

Modelling growth of Norway spruce on former agricultural lands in Latvia

Andis Zvirgzdiņš



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Andis Zvirgzdiņš

Supervisor: Urban Nilsson, SLU, Southern Swedish Forest Research Centre
Assistant supervisor: Jānis Donis, Latvian State Forest Research Institute "Silava"
Assistant supervisor: Ignacio Barbeito, SLU, Southern Swedish Forest Research Centre
Examiner: Eric Agestam, SLU, Southern Swedish Forest Research Centre

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Swedish University of Agricultural Sciences
Faculty of Forest Sciences
Southern Swedish Forest Research Centre

Abstract

Adequate growth forecasts are essential for forest management planning. In order to make such forecasts, accurate growth models are required. Due to the rapid growth of Norway spruce (L.) Karst. planted on former agricultural lands, existing growth models are unable to predict the development of Norway spruce with sufficient accuracy. Therefore, the aim of this study was to develop new height development and diameter models for Norway spruce up to 15 years of age. Data used in development of the models was obtained from twelve Norway spruce plantations established on fertile agricultural lands located in eastern Latvia. Height development was modelled using dynamic site equations derived using the generalized algebraic difference approach (GADA). In total fifteen different equations were estimated using non-linear least-square regression. Diameter models were developed using multiple linear regression. Subsequently, further development of the stands was simulated using stand-level management simulation tool StandWise of Heureka-DSS.

Of the fifteen tested equations, the best fit and prediction statistics were achieved using Chapman-Richards and Sloboda models. However, the best overall performance was demonstrated by Chapman-Richards model. Diameter was estimating with a linear regression model. Stand level projections showed that MAI_{max} for stands considered in this study varied between $14.7 - 17.6 \text{ m}^3 \text{ ha}^{-1} \text{ year}^{-1}$. According to LEV estimates, optimal rotation age of the stands varied between 41 – 48 years.

With the development of height and diameter growth functions, it is now possible to model development of planted Norway spruce stands from 5 years of age. Furthermore, further development of trees with estimated heights and diameters can be modelled using simulation systems such as Heureka-DSS.

Key words: Norway spruce plantations, young stands, height development, generalized algebraic difference approach, growth simulations

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List of abbreviations

AAL – Abandoned agricultural land

ADA – Algebraic difference approach

AIC – Akaike information criterion

CAI – Current annual increment

CSB – Central Statistical Bureau

DBH – Diameter at breast height

DSS – Decision Support System

GADA – Generalized algebraic difference approach

LEV – Land expectation value

LLC – Limited Liability Company

LSFRI – Latvian State Forest Research Institute

MAI – Mean annual increment

MPE – Mean prediction error

NFI – National Forest Inventory

NPV – Net present value

PCT – Pre-commercial thinning

PE – Prediction error

RMSE – Root mean squared error

SD – Standard deviation

SE – Standard error

1. Introduction

1.1 Norway spruce in Latvia: habitat and distribution

Like in many countries within boreal and boreo-nemoral regions of Europe, Norway spruce (*Picea abies* (L.) Karst.) is one of the most important tree species in Latvia both for economic and ecological aspects. Cultivation of Norway spruce in Latvia goes back a long way – with the first documented records made in the first forest inventories, conducted in the mid-19th century (Lībiete & Zālītis, 2007). Currently, according to NFI data, Norway spruce is the 3rd most common tree species in Latvian forests, accounting for 18.8 % of the total growing stock (CSB, based on NFI of 2014). Norway spruce is the most productive species in Latvia, with mean annual increment (MAI) of 7.8–8.8 m³ ha⁻¹ year⁻¹ on average, but on very suitable (fertile site conditions), MAI can reach up to 15 m³ ha⁻¹ year⁻¹ (Bisenieks, 1997; Zviedre, 1999). In terms of distribution of the species, Norway spruce can be found throughout the country (Fig. 1), what can be explained with favourable growth conditions in Latvia (Lībiete & Zālītis, 2007; Zeltniš, 2017).

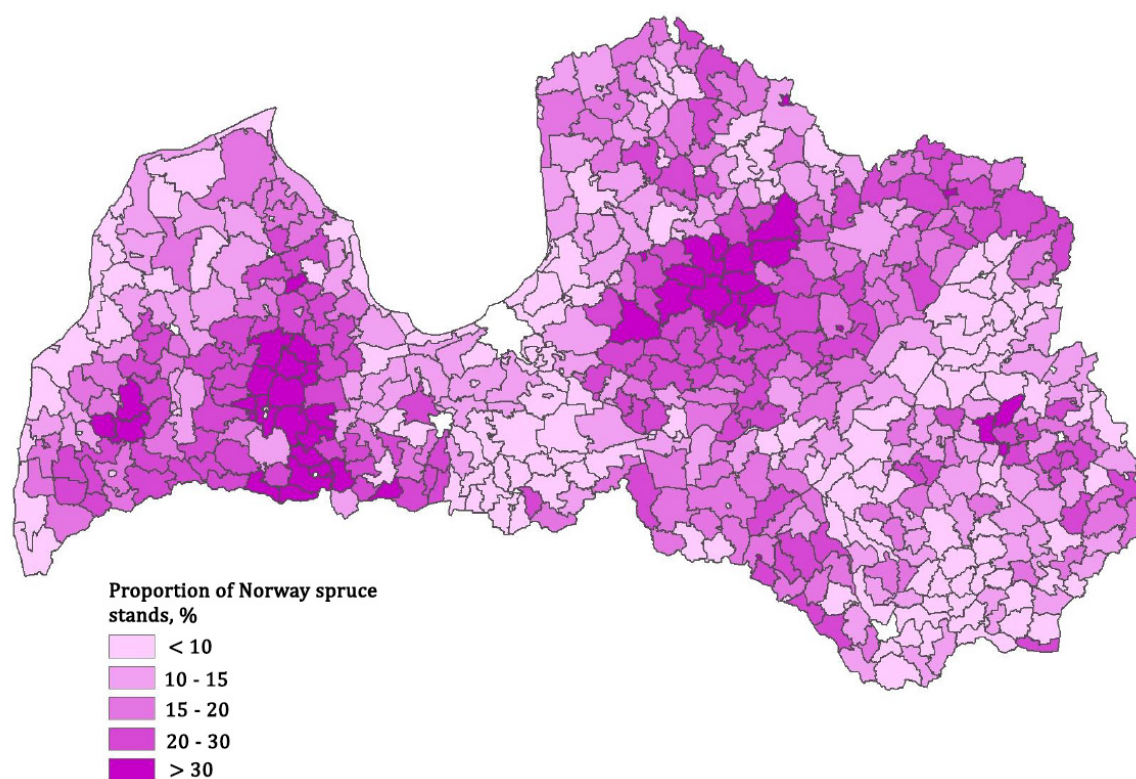


Figure 1. Proportion of Norway spruce stands in municipalities of Latvia (Pilvere, 2013).

The distribution of Norway spruce stands in Latvia is not uniform due to differences in suitability of growth conditions as well as due to implementation of management of different goals and intensity. Norway spruce can grow on a variety of site conditions forming both monocultures and mixed stands. In mixed stands it is most commonly found together with Scots pine (*Pinus sylvestris*), Silver birch (*Betula pendula*), Downy birch (*Betula pubescens*) and European aspen (*Populus tremula*) (Zeltniš 2017), but it can also be found in mixtures with Grey alder (*Alnus incana*) and Black alder (*Alnus glutinosa*), and in rare instances with

Pedunculate oak (*Quercus robur*) and European ash (*Fraxinus excelsior*). In a study conducted by Laiviņš (2005), he found that slightly higher proportion of Norway spruce stands in Latvia is observable on highland terrains due to more suitable and nutrient rich soil (clay loam and sandy loam) and more continental climate preferred by this particular species. In addition, Laiviņš (2005) indicated that the most favourable sites for Norway spruce are mesic.

1.2 Growth of Norway spruce

In general terms, Norway spruce is able to grow and show quality performance on a variety of site conditions (Caudullo *et al.*, 2015). In order for the development of Norway spruce to be successful, site conditions must meet the demands of the tree species over the whole rotation period (Rehsehuh *et al.*, 2017). In accordance with Bušs (1976; 1981), forest sites on fertile dry mineral soils (*Vr – Oxalidosa*, *Gr - Aegopodiosa*), wet mineral soils (*Vrs - Myrtilloso–polytrichosa*), drained mineral soils (*Ap - Mercurialiosa mel.*) and drained peat soils (*Kp - Oxalidosa turf. mel.*) are suitable for growing Norway spruce, while Zviedre (1999) indicated that forest sites on dry mineral soils and drained peat soils are the most favourable and productive for Norway spruce, but sites on wet mineral soils and peat soils are less suitable but capable of forming productive stands. In a more recent study by Lībiēte & Zālītis (2007), they determined that Norway spruce, as a dominant species, can form stands on fertile forest site types on dry mineral soils and both drained mineral and drained peat soils, what to a large extent confirms the findings of previous studies. The above said coincides with the fact that Norway spruce is capable of being productive on a variety of site conditions. However, in other studies conducted by Zālītis & Lībiēte (2003), it was determined that Norway spruce stands growing on wet mineral soils and drained peat soils are less stable and are under bigger risk of breakdown. As a reason for the increased risk of collapsing of the stands is believed to be root rot (Zālītis & Lībiēte, 2005).

Norway spruce is considered to be a late successional species (Bušs 1989; Nilsson *et al.*, 2012; Oberhuber *et al.*, 2015) with slow initial growth. Growth phase of young Norway spruce stands can be characterized by several stages. According to Lībiēte & Zālītis (2007), annual increment of Norway spruce ranges between 10 – 20 cm up until the trees have reached a height of approximately 2 m. Studies carried out in Latvia and abroad have shown that growth in the establishment phase can be affected by a variety of biotic and abiotic factors. Among the most important ones are water and nutrient availability (Zālītis & Lībiēte, 2005; Johansson *et al.*, 2011; 2012), climatic factors, soil properties and seedling characteristics (Johansson *et al.*, 2012), browsing, pine weevils and vegetation (Nilsson *et al.*, 2010).

Following the initial – slow growth phase, a phase of rapid growth ensues in which Norway spruce shows the highest increase in all stand parameters throughout its growth cycle. During this phase volume growth or current annual increment (CAI), on fertile sites, may reach up to 20 m³ ha⁻¹ year⁻¹ (Lībiēte & Zālītis, 2007). According to Lībiēte (2008), volume growth of Norway spruce is the highest while the mean height of the stand is between 12 – 17 m, often resulting in an accumulation of 200 m³ ha⁻¹ of volume, over the period of 10 years. However, in order to achieve such growth and yield, certain management needs to

be considered. In accordance to Zālītis & Lībiēte (2008), intra-specific competition is a decisive factor of the future growth and yield of stands. Therefore, it is recommended to carry out well-timed pre-commercial thinnings. The highest productivity of future crop trees (merchantable timber) can be achieved by reducing the number of trees to 1500 – 2000 trees ha^{-1} before the mean height of a stand reaches 5 m (Zālītis & Lībiēte, 2008). For instance, a young stand which has been thinned ($N=1500$, $H=5.9$ m, $\text{Age}=10$), under certain conditions, is capable of producing 18 % or $52 \text{ m}^3 \text{ ha}^{-1}$ more yield than the unthinned stand ($N=4000$, $H=4$ m, $\text{Age}=10$) (Zālītis 2006). Furthermore, stands where the mean height has reached or exceeds 10 m, thinning of the smallest trees has no significant effect on the growth of the dominant, future crop trees (Zālītis & Špalte, 2002; Zālītis & Lībiēte, 2008). Moreover, beneficial effect of pre-commercial thinning (PCT) on tree growth has been documented in other studies carried out in Latvia as well as in several foreign studies. It has proven to be an important silvicultural treatment for achieving the desirable structure, quality and yield of future stands (Bušs, 1989; Kuliešis & Saladis, 1998; Fahlvik *et al.*, 2005; Weiskittel *et al.*, 2011; Holmstrom *et al.*, 2016).

Norway spruce stands in the final stage, what according to Lībiēte & Zālītis (2008) occurs at the age of approximately 40 years, may differ partly due to implemented management. On high fertility sites, the total yield at the age of 40 can attain $350 \text{ m}^3 \text{ ha}^{-1}$. In part of the stands, intensive volume growth of around $10 \text{ m}^3 \text{ ha}^{-1}$ continues reaching a yield of up to $500 \text{ m}^3 \text{ ha}^{-1}$ at the end of the rotation (80 years), while in others, significant decline in growth can be observed with CAI being close to zero or even negative and stands on the brink of breakdown (Fig. 2) (Lībiēte & Zālītis, 2007; Lībiēte, 2008).

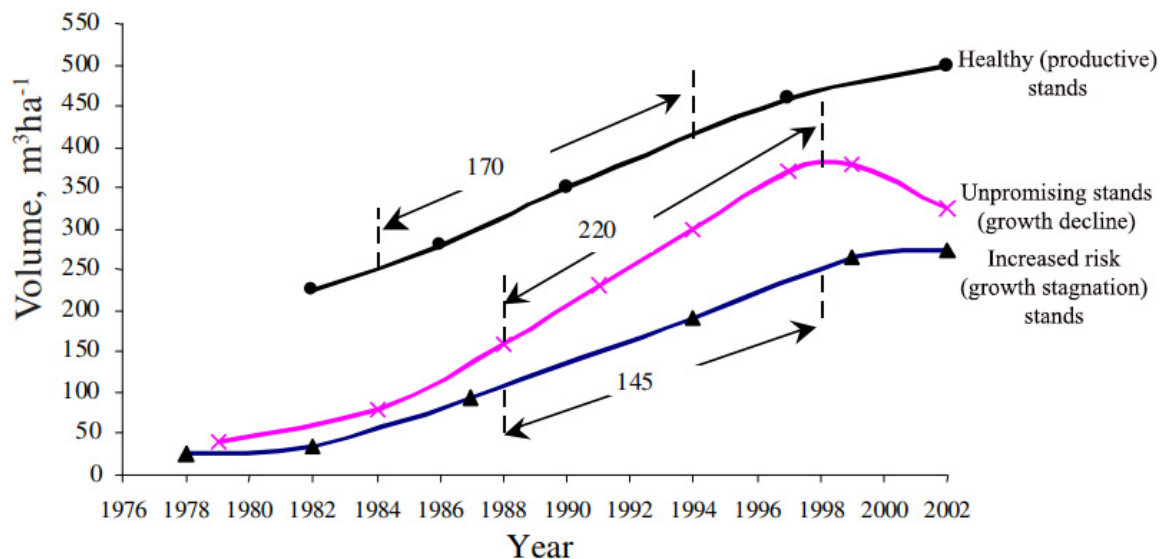


Figure 2. Volume growth trends in 30 – 50 year-old Norway spruce stands (Lībiēte & Zālītis, 2007).

Growth and yield of Norway spruce depends on several site (resource supply) and species (acquisition and resource-use efficiency) related factors. In a study conducted in Latvia, Lībiete & Zālītis (2007) determined that for 30-50 year old Norway spruce stands, largest reciprocal effect or 70 % of the variation of integral growth index $i \times r$ (i is annual ring mean width, r is linear correlation coefficient) of Norway spruce could be explained with the ecological requisites of the species, while growth conditions accounted for 30 % (Lībiete & Zālītis, 2007). According to this study, the lowest growth potential of Norway spruce was found for stands growing on drained peat soils, but the highest – for stands growing on drained mineral soils. Decline in production on peat soils could be explained with less suitable soil conditions, i.e. poorer aeration of soil and higher soil humidity in the top layer. In an earlier study by Zālītis (1968), it was determined that on drained peat soil, up to 15 m from the draining-ditch Norway spruce shows the same yield as Scots pine, but beyond, volume growth of Norway was considerably lower than for Scots pine. With that being said, formation of Norway spruce stands on wet mineral soils and drained peat soils is not deemed as imprudent, but species ecological requirements in conjunction with certain management operations should be considered when establishing stands on the respective site conditions.

1.3 Establishment and growth of Norway spruce on AAL

In Latvia, there are more than 300 thousand ha of abandoned agricultural land (AAL), with the highest proportion being in the region of Latgale ~ 27 % (MEPRDRL, 2016). High soil fertility and potentially high production capacity are probably the main reasons for increased interest in growing Norway spruce on AAL. In addition, since 2015 State and EU subsidies are available for establishing forests on former agricultural lands. Furthermore, Norway spruce is one of the most commonly used tree species in plantation establishment, accounting for 35 % or 945 ha planted in 2017 (State Forest Service, 2018).

Norway spruce can grow on a variety of site conditions; however, it best performs on mesic, nutrient-rich soils. Having said that, excessively wet, waterlogged sites as well as nutrient-poor sites should be avoided. Planting Norway spruce on unsuitable sites (parts of the stand) may result in increased mortality of the seedlings, growth stagnation and reduced production, as seen in some of the stands surveyed in this study. According to Daugaviete *et al.* (2017), selection of suitable sites may increase the production of Norway spruce established on plantations by 61 %.

Selecting genetically superior forest reproductive material is of considerable importance in increasing productivity of Norway spruce plantations. In addition, tree selection and genetic modification may increase the resistance of tree species against certain diseases, provided that a sufficient variation of clones is maintained (Daugaviete *et al.*, 2017). The gain in yield using genetically modified material in Latvia is around 10 % (Zeltiņš, 2017). Gain in yield may also depend on site properties and geographical position of the sites. According to Daugaviete *et al.* (2017), use of genetically improved seedlings may increase the production of Norway spruce established on agricultural lands by 17 %.

Soil scarification is one of the most important silvicultural practices to increase the success of seedling establishment (Johansson *et al.*, 2012). Soil scarification can improve

seedling establishment and survival by: 1) reducing competition from field vegetation; 2) Increasing soil temperature; 3) Decreasing soil density; 4) Increasing soil moisture and mineralization; 5) reducing seedling mortality caused by pine weevil; 6) reducing frost damage (Sundheim Fløistad *et al.* 2017). In addition, in both Latvian and Swedish studies it has been found that, soil mechanical preparation has a positive effect on the height growth of Norway spruce (Johansson *et al.* 2012; Lazdiņa, 2018).

Vegetation on the ground cover is a serious competitor for young Norway spruce seedlings. According to Daugaviete *et al.* (2017), ground vegetation restricting measures are necessary to promote root development and further growth of Norway spruce seedlings. In Latvia, use of herbicides on agricultural lands is permitted, therefore it is highly recommended to eradicate weeds on agricultural lands using herbicides before planting. Researchers from Latvian State Forest Research Institute (LSFRI) have found that 3 years after planting on average, the survival rate of Norway spruce seedlings using herbicides as weed-restricting treatment, is within 99 % (Daugaviete *et al.*, 2017).

After the establishment phase, it does not take long until the intra-specific competition starts between the trees. Competition between trees can be regulated by performing pre-commercial thinnings (PCT's). As indicated before, well-timed PCT's are of high importance for the development of future crops trees (merchantable timber). According to Daugaviete *et al.* (2017), well-timed thinning operations (PCT's; commercial thinnings) may increase the production of future crop trees by 8 %.

Productivity of Norway spruce plantations can also be increased by fertilization. However, type of fertilizer, quantity of fertiliser used as well as time of application (frequency) has to be considered to achieve best results overall. Fertilization has been found to have a notable effect on growth of Norway spruce on forest sites in Latvia (Jansons *et al.*, 2016; Okmanis *et al.*, 2016). As reported by Daugaviete *et al.* (2017), the largest height and diameter increment was observed on fertilized Norway spruce sites, compared on unfertilized ones.

1.4 Growth and yield models

Growth of the trees is an immensely complex, biological process in which they extend their successive layers of growth in both height and in diameter over a given time period (Punches, 2004), whereas yield is a measure, which quantifies these layers of growth or final dimensions of trees at the end of a certain period specifying the total volume production. Consequently, growth and yield models are used to describe the complex processes in the forest and predict the future status of the forest at any given time. Both growth and yield are mathematically related – growth is determined by solving a yield equation (if yield is y , growth is the derivative dy/dt), which in many cases allows to transform models from one form to another (Vanclay, 1994).

There are different kind of growth models, differing in the type of data used and the method of construction (Burkhart & Tome, 2012). Commonly, models are divided into two groups: empirical and mechanistic models, but as indicated by Weiskittel *et al.* (2011), a

more useful metric of differentiation would be by dividing forest stand models into four categories: 1) statistical, 2) process, 3) hybrid and 4) gap models since all models are on a spectrum of empiricism (Weiskittel *et al.*, 2011). The word *empirical* refers to a method of obtaining data using observation senses and scientific instruments if necessary. In forestry, this method has been and still is an integral part in construction of growth models as most models are built upon observations collected during surveys or different experiments (Egbäck, 2016). Furthermore, collection and analysis of this type of population (trees in a forest stand) descriptive data allows to estimate statistical variability of certain parameters (Weiskittel *et al.*, 2011). Depending on the level of detail they provide, several modelling approaches can be distinguished. Fundamentally, two types of forest growth models can be recognized: individual-tree and whole-stand (Munro, 1974), but no classification system of modelling approaches can be fully satisfactory as there are various modelling approaches differing in level of resolution or modelling entity. (Burkhart & Tome, 2012). Most common modelling approaches can be regarded in Figure 3.

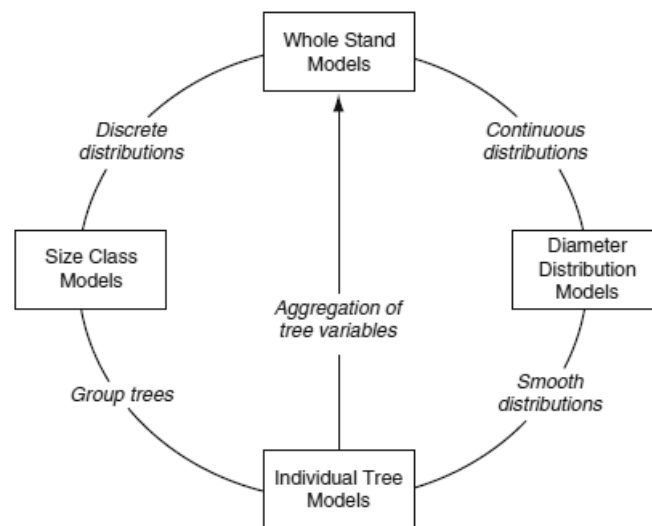


Figure 3. Classification of the most common modelling approaches and linkages between them (Burkhart & Tome, 2012).

Whole stand models are some of the oldest and most widely used growth and yield models (Weiskittel *et al.*, 2011). It goes way back, when the first yield tables were developed using data obtained from sample plots located in stands of varying ages representing various site qualities (Burkhart & Tome, 2012). Whole stand models are easy to develop and apply. In addition to that, they are often highly accurate in describing single species, even-aged stands. Whole-stand growth models can be constructed using stand variables such as basal area, site index, stand density index, stand diameter, stand age and number of stems (Sharma, 2013). Notwithstanding, such models have a limited ability to describe complex stand structures (Weiskittel *et al.*, 2011; Qin & Cao, 2006; Garcia 2001), mixed species, and forest silvicultural treatments accurately which can be explained by the applied methods describing such conditions. Accordingly, in many regions of the world, individual tree models, also known as tree-level models have become like the new standard for modelling growth and yield. The reason for this is their flexibility and ability to accurately characterize growth

under a range of stand conditions (Weiskittel *et al.*, 2011). Using tree-level based modelling it is possible to describe different combinations of species mixtures and stand structures, management regimes and regeneration methods (Burkhart & Tome, 2012). In addition, tree-level models are superior to other modelling approaches in characterizing impacts of different damaging agents (Weiskittel *et al.*, 2011). However, tree-level modelling approach requires more detailed data for their development which in most cases makes the data collection procedure more expensive. Furthermore, error compounding is potentially greater for tree-level models (Weiskittel *et al.* 2011), which can be particularly observed when this detailed information obtained from tree-level models is used in the construction of stand-level models (Cao, 2014). Tree level models can either be distance dependent and distance independent. Distance dependent models require spatial coordinates of all trees, while distance-independent models assume and average spatial pattern of trees (Weiskittel *et al.* 2011). Most tree-level models are based on radial growth at breast height due to the fact that radial growth is more affected by competition than height growth (Sharma, 2013). As a result, only few individual tree level models have been constructed using height growth as base variable (e.g. Pretzsch *et al.*, 2002; Fahlvik & Nyström, 2006; Nord-Larsen, 2006b; Uzoh and Oliver, 2006; Ritchie and Hamann, 2008; Vaughn *et al.*, 2010).

Irrespective of their level of detail, growth models can also be categorized between deterministic or stochastic. Deterministic growth models, regardless of the number of modelling times, will always return the same output value, provided that the initial values remain unchanged. On the contrary, stochastic models, by incorporating a random element, will return multiple, different predictions in successive runs each with a specific probability of occurrence (Weiskittel *et al.*, 2011; Vanclay, 1994). For instance, contrary to deterministic models, which estimate only one result of the expected growth of a forest stand, stochastic models, by including natural variation characteristic of the environment, estimate several, different growth scenarios. Despite differences between both types of models, they can be used complementarily, providing a more complete understanding of growth processes (Vanclay, 1994).

1.4.1 Height growth modelling

Height is an immensely important tree and site descriptive variable and is often used as input parameter of models or decision support systems (Sharma & Breidenbach, 2015). Various methods and modelling approaches have been used to capture height growth patterns and establish reliable tools, which could be used for forest management planning related decision-making, i.e. scheduling of harvesting operations, planning and evaluation of different silvicultural treatments, etc.

Height growth of co-dominant and dominant trees is the most commonly used indicator of site quality. Dominant height is believed to be independent of stand density and thinning operations, provided it is thinning from below (Skovsgaard & Vanclay, 2008, Burkhart & Tome 2012). In addition, there is strong correlation between height growth and volume production. Therefore, dominant height at a given reference age may be used as a stand productivity descriptive measure (Sharma, 2013). The top height-production relationship is based on Eichhorn's law or Eichhorn's hypothesis (Eichhorn, 1904),

indicating that the total production of a fully-stocked stand (net volume production) is a function of its height (Fontes *et al.*, 2003).

Dominant height growth models or site index models can be developed using two modelling approaches: the traditional – base-age specific approach and base age invariant approach. Models based on base-age specific approach are developed using height and a common reference age. Although, base age-specific modelling approach has been widely used for modelling site index, in certain cases, it suffers from inaccurate predictions. Due to the common reference age, in case height is not measured at that specific age, this method requires the use of interpolation or extrapolation to determine height (Sharma, 2013), thus leading to biased prediction results (Weiskittel *et al.*, 2011). As a result, Bailey and Clutter (1974) developed base-age invariant modelling approach – algebraic difference approach (ADA), which allows the use of various types of data for application and parametrization as well as height can be predicted at different ages of the stand (Weiskittel *et al.*, 2011) without significantly affecting the accuracy of predictions. In ADA modelling approach, base equations are described by one site-specific parameter, for which a solution is derived from the base model (Liziniewicz *et al.*, 2016). Models derived from ADA approach may produce curves with a single asymptote, also known as anamorphic curves (Sharma, 2013). Based on the work of Bailey & Clutter (1974), Ciezewski and Bailey (2000) introduced a generalization of ADA – generalized algebraic difference approach (GADA). It was done by expanding the base model with a purpose to make data and theories of modelled phenomena more inclusive. Compared to ADA, GADA provides more flexible dynamic equations, suitable for a wide range of growth and yield models (Ciezewski 2002). The GADA method allows derivation of flexible dynamic functions, which are base-age invariant with predicted height equal to site index at base age (Burkhart and Tome 2012). In GADA modelling approach, more than one site-specific parameter can be solved with an equation derived from the base model (Liziniewicz *et al.*, 2016). In case more than one site-specific parameter is solved with an equation, generated models are polymorphic with varying asymptotes (Ciezewski, 2003; Ciezewski *et al.*, 2007, Liziniewicz *et al.*, 2016). GADA modelling approach has been widely used in the construction of dominant height (site index) growth models for different species and has proven to be reliable (Adame *et al.*, 2006; Martin-Benito *et al.*, 2008; Bravo-Oviedo *et al.*, 2008; Nord-Larsen *et al.*, 2009; Sharma *et al.*, 2011; Perin *et al.*, 2013; Liziniewicz *et al.*, 2016; Feracco Scolforo *et al.*, 2016).

1.4.2 Growth modelling in Latvia

Adequate growth forecasts are essential for forest management planning (Donis, 2016). Although, several studies have been carried out on the growth of Norway spruce in Latvia (Zālītis 1968; Zālītis, 2006; Zālītis & Lībiete, 2007; Zālītis & Lībiete, 2008; Lībiete, 2008), range of models that would accurately describe different growth-related processes is imperfect. Moreover, the changing climate has resulted in new weather patterns (Jansons 2011; 2015, Avotniece *et al.*, 2017) and trees no longer follow the growth patterns they did 20 – 30 years ago, therefore, there is a need to update the existing growth models as well (Donis *et al.*, 2015; Donis & Šņepsts 2015; Donis, 2016).

Probably, the oldest and most widely used tools to predict forest growth are growth and yield tables. In the most commonly used growth and yield tables, forest stand was structured into dominant layer and sub-layer (suppressed trees). Dominant layer was described by mean height and diameter, basal area, form factor, number of stems and volume while sub-layer was only explained by volume. Furthermore, these growth and yield tables only described fully stocked even-aged monocultures. Growth and yield tables used in Latvia were obtained by interpolating the growth and yield tables initially constructed by Vargas de Bedemar (1850) for N-W regions of Europe and by Schwappach (1908) for Northern Germany (Skudra, 2005). However, growth and yield tables suffer from a substantial drawback – they are unable to predict the growth of diverse, structurally complex forest stands with sufficient accuracy.

Requirements of modelling dataset (type, quality, size) largely depend on the type of model constructed (Weiskittel *et al.*, 2011). In Latvia, most models are statistical models based on empirical data. Current annual increment (CAI) growth models constructed in Latvia may be based on different data collection methods: permanent plot method, sample tree method, boring (increment core) method and cameralistic method (Donis *et al.*, 2015, Liepa, 2018). Hitherto, growth (CAI) models used in Latvia (Matuzānis 1988, Liepa 1996) have been constructed to a large extent based on increment cores obtained from one-time sample plots visited around 1960's – 1970's (Donis 2016). These sample plots were placed in stands varying in age, density and site index (Matuzānis, 1985). According to Donis (2016), these models are unable to accurately predict mortality and thus growth as a whole. Bisenieks (2010) considers that data from periodically re-measured long-term permanent sample plots is *sine qua non* in the development of reliable growth models. Furthermore, as reported by Donis (2015), National Forest Inventory (NFI), which is a permanent and repeated systematic sample plot inventory, provides most of the variables needed to develop growth models. Consequently, NFI data has been used in the development of several growth models, e.g. Donis *et al.*, (2015) developed CAI and natural mortality models for six different species, including Norway spruce. Equations developed in the study by Donis *et al.*, 2015 can be used to forecast growth of stand strata, but they are not suitable for predicting mortality caused by natural disturbances such as forest fires, storms, etc. In the most extensive study so far, Donis (2016; 2017; 2018) worked on the development and improvement of multiple stand level growth models. Based on data obtained from NFI, mean height (H_{mean}) and dominant height (H_{dom}) growth models as well as basal area (BA) and quadratic mean diameter (D_q) growth models were developed for Norway spruce and five other tree species. Height growth models (H_{dom} , H_{mean}) were developed using GADA modelling approach, as suggested in previous reports (Donis, 2011; 2014; 2015). GADA is a flexible modelling approach, which allows to construct height growth models using only stand height and age, without using information about site index (SI) (Donis, 2018).

In order to be able to accurately describe complex stand structures, species mutual interactions as well as effect of different management regimes of varying intensity, individual-tree models are needed. Based on the knowledge obtained from analysing individual-tree models constructed in Sweden and Finland, Donis (2018) has developed

several individual-tree models for Latvian conditions. For modelling of individual-tree height growth, Donis (2018) provisionally recommends the use of mean height model developed using Hossfeld IV equation of GADA.

1.5 Simulations of growth and yield using forest growth simulators

Long-term forest management planning is an immensely complex task (Wikström *et al.*, 2011), that requires accurate forecasts of the further development of forest trees and stands. Such forecasts can be obtained by forest growth simulators, which using the underlying models, biometrically and mathematically reproduce the biological growth process (Blatert *et al.*, 2016). Growth and yield forecasts are usually simulated periodically, i.e. all stand descriptive variables (height, diameter, basal area, volume growth, etc.) are updated after a certain time period, normally 5 years as minimum. In addition, forest growth simulators provide an opportunity to implement different silvicultural treatments and simulate different management regimes. Ideally, in simulations, it is possible to determine not only future growth and yield, but variety of economic and ecological indicators, necessary in the adoption of decisions related to forest management planning.

1.5.1 The Heureka Forestry Decision Support System (DSS)

Heureka-DSS is an empirically based forest growth simulator, developed and hosted by Swedish University of Agricultural Sciences (Wikström *et al.*, 2011; Subramanian, 2016). Heureka-DSS encompasses many of the empirical growth models developed in Sweden (Fahlvik *et al.*, 2014; Egbäck, 2016). The system consists of three main applications:

- **Heureka StandWise** – a stand-level management simulation and visualization tool, which allows to simulate development of one stand at a time. Stand development is simulated periodically, with minimum time step of five years. During the simulation process, different silvicultural treatments can be specified, period by period.
- **Heureka PlanWise** – a forest-level (landscape-level) analysis and planning tool, that provides an opportunity to simulate development of several stands at a time with a minimum time span of five years. In addition to the possibility to analyze different management scenarios, this application has a built-in optimization tool.
- **Heureka RegWise** – a regional-level (national-level) planning tool for long-term analysis of large geographical areas. RegWise long-term forecasts are mainly based on national forest inventory (NFI) data, but also digital maps and data obtained from remote sensing are used. Regwise allows to forecast future status and production of different ecosystem services of large scale forest areas, depending on the chosen forest management approach (SLU, 2016; Subramanian, 2016).

All three of the applications listed above use the same set of sub-models (Fig. 4) for predicting site and stand data (e.g. site index, tree age), growth and mortality (Fahlvik *et al.*, 2014). More in-depth description of the underlying sub-models of Heureka-DSS can be found in the studies of Fahlvik *et al.* (2014) and Subramanian (2016).

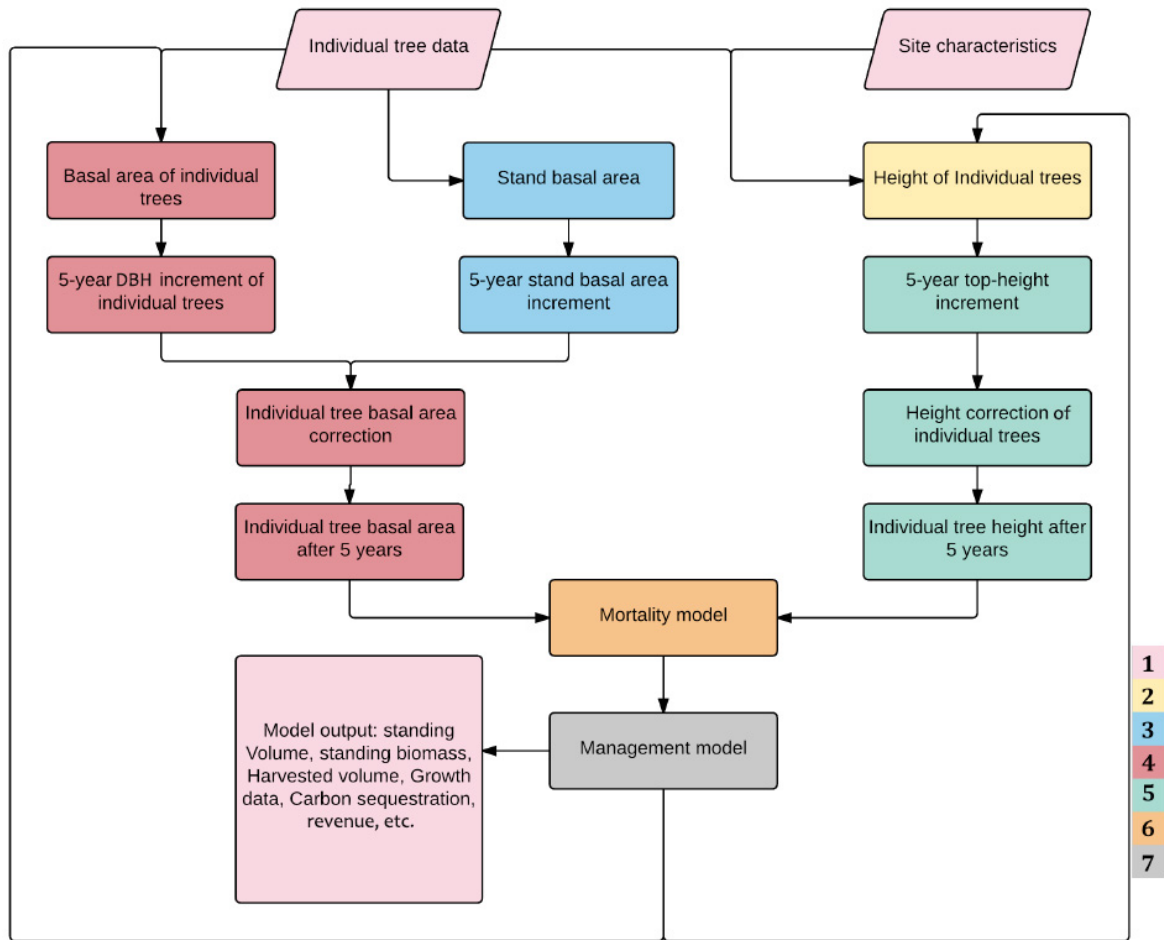


Figure 4. Schematic diagram of Heureka-DSS and its underlying models. *Different colours in the scheme represent different components (sub-models) of Heureka simulation system. They are as follows: input-output module (1), estimation of individual tree heights at the start of the simulation (2), stand basal area increment function (3), five-year DBH increment functions for individual trees (4), height increment function for individual trees (5), mortality model (6) and management model (7) as adopted from Subramanian (2016).*

Simulation results of the analyzed stands or forest areas are given in the form of tables, maps and graphs. Different forest stand descriptive variables, such as *Stand age (years)*, *Dgv (cm)*, *Hgv (m)*, *Volume (m³ha⁻¹)*, *Net Revenue (SEK/ha-1)*, can be selected by the user, as well as graphs and maps can be created or modified at its own discretion. Furthermore, different silvicultural treatments can be implemented or management scenarios generated using built-in control categories of Heureka-DSS.

1.6 Aims of the thesis

The main objective of this study was to study growth of Norway spruce planted on former agricultural lands and develop diameter and height development models describing growth from five to fifteen years of age. Subsequently, with the set of models developed to estimate height and diameter of trees at the age of fifteen years, analyse further stand development using stand growth simulator.

The main aims were:

1. Construct a model for height development of Norway spruce from five to fifteen years of age.
2. Develop a model, which would accurately estimate DBH of Norway spruce at the age of 15 years.
3. Evaluate stand growth and determine the optimal rotation age of stands considered in this study.

1.6.1 Schematic diagram of thesis structure

The process of developing this master's project, including all tasks, is depicted schematically in Figure 5. The work consists of 4 main stages: the first two stages are *Data collection* and *Data preparation*, where data is being prepared and arranged for the construction of the models. The last two: *Modelling* and *Simulations* are stages where the tree main tasks of this study are fulfilled.

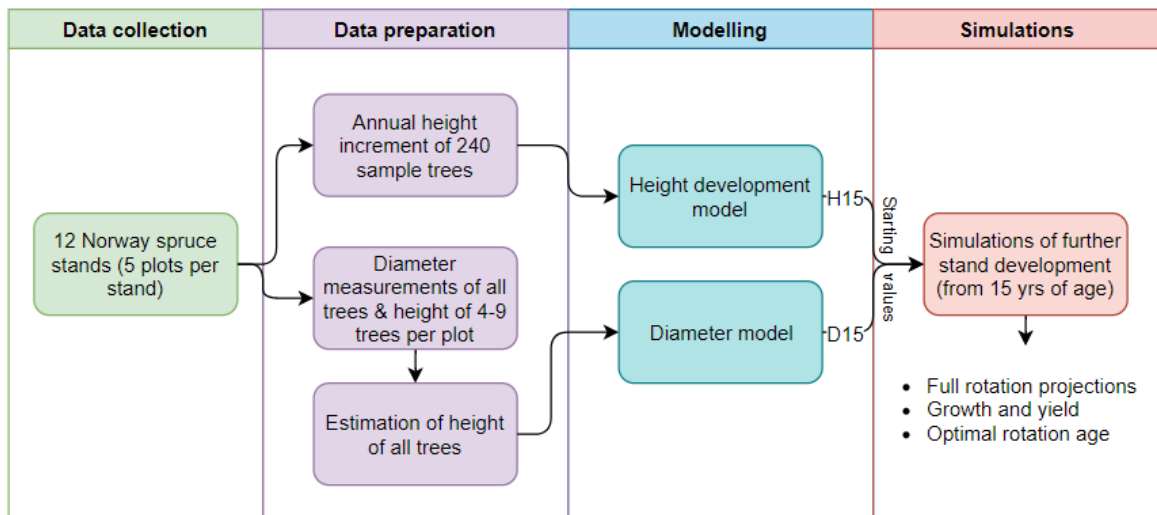


Figure 5. Schematic diagram showing the order of tasks to be performed in this work.

2. Materials and methods

2.1 Study area

The study was carried out in the eastern part of Latvia – Latgale – a region located at the frontier of Belarus and Russia. In total, 12 Norway spruce stands were selected within the latitude of 56°12' and 56°35' and longitude of 27°44' and 27°58', located in the 3 easternmost counties of Latvia – Ludza, Cibla and Zilupe (Fig. 6). Typically for the continental climate, the climate in this part of the country is more diverse than it is in the rest of the country, i.e. summers are hotter, winters are more severe and the temperature changes more drastically throughout the year with an average annual temperature being approximately + 5.2 °C. (National encyclopedia, 2019). Mean annual precipitation for the area selected for this study (Fig 6., highlighted in red) is between 600 – 650 mm year⁻¹, which is slightly lower than the mean annual precipitation in the whole country. The area is located relatively high, 160 m a.s.l., while most of the country's territory (73,5 %), is below 120 m a.s.l. According to genetic soil classification of Latvia, soil in this highland is mainly podzolic (sod-podzolic, sod-podzolic gley soil, eroded podzolic soil) with sandy loam and loam as predominant constituent of soil parent rock.

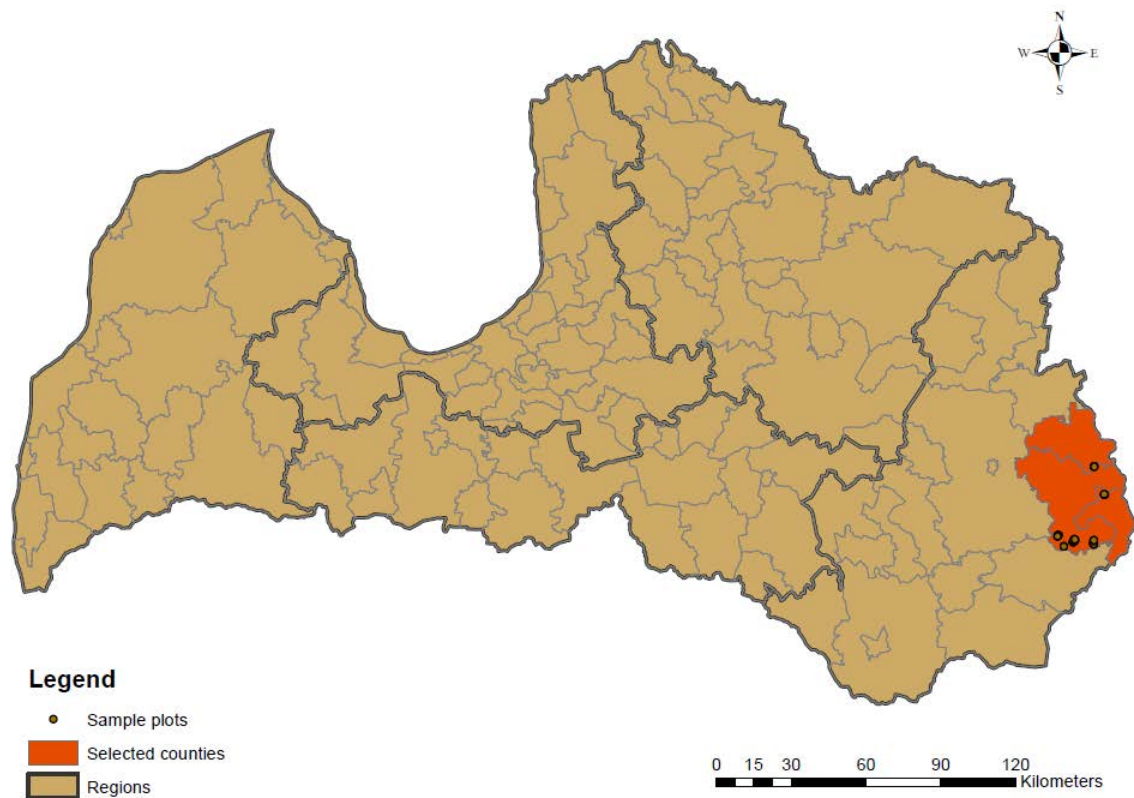


Fig. 6. Geographical location of the study area.

2.2 Selection of the stands and site description

All twelve stands were selected within the area managed by Skogssällskapet Latvia, LLC (Table 1). Several criteria such as age, species composition, forest type was considered when selecting stands. Only pure Norway spruce stands were considered, which in this

research were defined as stands where an admixture of other tree species was below 15 % of number of trees. Further on, stands were selected by soil type. In this study, we focused on stands growing only on dry mineral soils, which according to Latvia's forest typology developed under guidance of Bušs in 1976 (Liepa *et al.* 2014) could be classified as – Dm (*Hylocomiosa*) and Vr (*Oxalidosa*), the two most common forest types found in Latvia. In Latvia these forest types are often dominated by Norway spruce either in monocultures or in mixtures with other species. *Hylocomiosa* forest types most often are found on sandy loam, sandy soils but *Oxalidosa* on clay loam or clay soils. Forests on wet or drained soils were not considered in this research, because the data was not large enough to include soil moisture class in the models. Because many stands were established on former agricultural lands in the early 2000s, the age of the stands varied from thirteen to fifteen years. All of the stands were established by planting (2500 seedlings per ha) and most of the stands have undergone a thorough pre-commercial thinning, but some had only been partially pre-commercially thinned.

Table 1. Selected Norway spruce stands

Block	Compartment	Area	Age	Forest type	Composition	Coordinates	
						Latitude, N	Longitude, E
1	79	8.44	15	Dm	1.00NS	56.2246	27.8374
1	68	3.93	14	Dm	1.00NS	56.2246	27.9711
5	5	4.98	15	Vr	1.00NS	56.2156	27.9681
5	12	4.4	15	Vr	1.00NS	56.2114	27.9715
1	14	3.82	15	Vr	1.00NS	56.2323	27.8460
1	19	5.68	15	Vr	1.00NS	56.2309	27.8111
2	16	6.89	15	Vr	1.00NS	56.2508	27.7432
2	17	3.9	15	Vr	1.00NS	56.2482	27.7423
2	18	5.5	15	Vr	1.00NS	56.2462	27.7415
12	14	2.74	15	Vr	1.00NS	56.2096	27.7764
1	19	6.8	13	Vr	1.00NS	56.4910	28.0023
2	1	3.88	13	Vr	1.00NS	56.3888	28.0562

Note: Vr – Forest type *Oxalidosa*, Dm – Forest type *Hylocomiosa*; 1.00NS – 100% Norway spruce; Age was specified at the time of measurements (2018).

2.3 Data collection

Five sample plots with a radius of 5.64 m (100 m²) were placed in every stand. The location of the sample plots was generated using geospatial processing tool ArcMap. After placing a buffer zone of ten m from the edge of the stands, sample plots were placed with a quadratic spacing of thirty m. In the sample plots, all trees above two cm in DBH were cross-calipered and depending on the diameter distribution and species present in the plot, height was measured for four to nine trees using a Haglöf Vertex IV hypsometer. Thereafter, two dominant and two co-dominant trees were chosen and cut with a chainsaw. These trees were delimbed, leaving around 5 - 10 cm long twigs so that it was possible to determine positions of the whorls. Following delimbing, annual height growth was measured for every sample tree by attaching a measuring tape to the top of the tree and registering length at every whorl down to the root collar. But in order to determine height increment for every year, height of

each whorl was calculated going backwards (starting from root collar). Age was recorded by counting tree annual rings on the stump.

2.4. Estimation of height of all calipered trees

Due to the difficult and time-consuming procedure of measuring individual tree height, in stands considered in this study, height was recorded for 4 – 9 trees per plot. However, for starting values in Heureka simulations and for calculation of variable H_{sum} of diameter model, it was necessary to determine height of all the trees present in the sample plots. In order to determine height of all trees present in the sample plots, DBH–height relationship was estimated for each sample plot of each stand using height curve for Norway spruce developed by Näslund (1936).

$$H = \frac{D^3}{(a + b * D)^3} + 1.3, \quad (1)$$

where H is height of the tree (m), D is diameter at breast height (cm) and a and b are coefficients of the model. Data from trees with both height and diameter measurements was used for constructing the models. With newly obtained equations height was estimated for all the trees, which had their diameter measured.

2.5 Models

Two different type of models were developed in this study, describing development of planted Norway spruce on former agricultural lands. Height development models were constructed from five to fifteen years of age using height increment data of 240 sample trees. Diameter models were developed to estimate DBH at the age of fifteen years using measured diameters and tree heights calculated with the DBH–height function.

2.5.1 Height development model

Based on scientific knowledge in the field of research topic and previous studies (Cieszewski *et al.*, 2007; Liziniewicz *et al.*, 2016; Bravo-Oviedo *et al.*, 2008; Scolforo *et al.*, 2016; Martin-Benito *et al.*, 2008; Sharma *et al.*, 2011) in which this method has been used and proven to be capable of achieving good results, the generalized algebraic difference approach (GADA) was used in this study. GADA models used in this study are either based on base equations of fractional form (Hossfeld, King-Prodan and Strand) or exponential form (Chapman-Richards, Korf and Sloboda). In total, fifteen different equations, adopted from Sharma *et al.* 2011 and Liziniewicz *et al.* 2016, were tested in this study (Table 2). Amongst fifteen tested equations, five of them were GADA formulations of Chapman-Richards growth equation (equations (F01 – F05)), seven of them (equations (F06 – F12)) were derived from three different base equations of Hossfeld, including F06, developed by Elfving and Kiviste (1997). Of the remaining five equations, two of them were GADA formulations of Korf (F13 – F14) and the last three (equations (F15 – F17)) were GADA formulations of King-Prodan, Sloboda and Strand base equations respectively. The equations presented in this study can be defined by their parameters of the base model form (a_1, a_2, \dots, a_n and H, S, T) and global parameters of GADA formulations (T_0, T, H_0, H).

Table 2. Base models and generalized algebraic difference models (GADA) used in this study

Base model form	Site-specific parameters	Solution for theoretical variable X	GADA model form used in estimation of the parameters	
Chapman-Richards: $H = a_1(1 - e(-a_2T))^{a_3}$	$a_1 = X$	$X_0 = \frac{H_0}{(1 - \exp(-b_2T_0))^{b_3}}$	$H = \left(\frac{1 - \exp(-b_2T)}{1 - \exp(-b_2T_0)} \right)^{b_3}$	(F01)
	$a_2 = X$	$X_0 = \frac{-\ln(1 - (H_0/b_1)^{1/b_3})}{T_0}$	$H = b_1 \left(1 - \left(1 - \left(\frac{H_0}{b_1} \right)^{1/b_3} \right)^{T/T_0} \right)^{b_3}$	(F02)
	$a_3 = X$	$X_0 = \frac{-\ln(H_0/b_1)}{\ln(1 - \exp(-b_2T_0))}$	$H = b_1 \left(\frac{H_0}{b_1} \right)^{\frac{(\ln(1 - \exp(-b_2T)))}{(\ln(1 - \exp(-b_2T_0)))}}$	(F03)
	$a_1 = \exp(X)$ $a_3 = b_2 + \frac{b_3}{X}$	$X_0 = \frac{1}{2} \left(\psi + \sqrt{\psi^2 - 4b_3\Phi} \right)$ where $\psi = \ln H_0 - b_2\Phi$ and $\Phi = \ln(1 - \exp(-b_1t_0))$	$H = H_0 \left(\frac{1 - \exp(-b_1T)}{1 - \exp(-b_1T_0)} \right)^{(b_2 + b_3/X_0)}$	(F04)
Hossfeld based model of Elfving and Kiviste (1997) $H = \frac{a_1}{1 + a_2T - a^3}$	Solved with an assumption that $a_2 = a_3/S$		$H = \frac{H_0 + d + r}{2 + (4b_3/T^{b_2})/(H_0 - d + r)},$ where $d = \frac{b_1}{A_{si}^{b_2}}$ and $r = \sqrt{(H_0 - d)^2 + 4b_3H_0T_0^{-b_2}}$	(F05)

Table 2. (continued)

Base model form	Site-specific parameters	Solution for theoretical variable X	GADA model form used in parameter estimation
Hossfeld: $H = \frac{a_1}{1 + a_2 T^{-a_3}}$	$a_1 = b_1 + X$ $a_3 = b_2/X$	$X_0 = \frac{1}{2} \left(\psi + \sqrt{\psi^2 + 4b_2 H_0 T_0^{-b_3}} \right),$ where $\psi = H_0 - b_1$	$H = \frac{b_1 + X_0}{1 + b_2/X_0 T^{-b_3}} \quad (\text{F06})$
	$a_1 = b_1 + X$ $a_3 = b_2 X$	$X_0 = \frac{H_0 - b_1}{1 - b_2 H_0 T_0^{-b_3}}$	$H = \frac{b_1 + X_0}{1 + b_2 X_0 T^{-b_3}} \quad (\text{F07})$
	$a_2 = X$	$X_0 = T_0^{b_3} \left(\frac{b_1}{H_0} - 1 \right)$	$H = \frac{b_1}{\left(1 - \left(1 - \frac{b_1}{H_0} \right) \left(\frac{T_0}{T} \right)^{b_3} \right)} \quad (\text{F08})$
Hossfeld: $H = \frac{T^2}{a_1 + a_2 T + a_3 T^2}$	$a_2 = X$ $a_3 = b_1 + b_2 X$	$X_0 = \frac{T_0^2 (1 - b_1 H_0) - b_1 H_0}{H_0 T_0 (1 + b_2 T_0)}$	$H = \frac{T^2}{b_1 (1 + T^2) + X_0 T (1 + b_2 T)} \quad (\text{F09})$
Monserud (1984) derived by Cieszewski (2001): $H = \frac{a_1 S^{a_2}}{1 + \exp(a_3 - a_4 \log T - a_5 \log(S))}$	S^a	$X_0 = (Y_0 - b_1) + \sqrt{(Y_0 - b_1)^2 + 2b_2 H_0 T_0^{-b_3}}$	$H = \frac{T^{b_3} (T_0^{b_3} X_0 + b_2)}{T_0^{b_3} (T^{b_3} X_0 + b_2)} \quad (\text{F10})$
Korf: $H = a_1 \exp(-a_2 T^{-a_3})$	$a_1 = \exp(X)$ $a_2 = \frac{(b_1 + b_2)}{X}$	$X_0 = \frac{1}{2} T_0^{-b_3} \left(\psi + \sqrt{4b_2 T_0^{b_3} + (-\psi)^2} \right),$ where $\psi = b_1 + T_0^{b_3} \ln(H_0)$	$H = \exp(X_0) \exp \left(- \left(\frac{b_1 + b_2}{X_0} \right) T^{-b_3} \right) \quad (\text{F11})$

Table 2. (continued)

Base model form	Site-specific parameters	Solution for theoretical variable X	GADA model form used in parameter estimation
	$a_2 = X$	$X_0 = -\ln\left(\frac{H_0}{b_1}\right)T_0^{b_3}$	$H = b_1 \exp\left(\ln\left(\frac{H_0}{b_1}\right)\left(\frac{T_0}{T}\right)^{b_3}\right)$ (F12)
King-Prodan: $H = \frac{T^{a^1}}{a_2 + a_3 T^{a^1}}$	$a_2 = b_2 + b_3 X$ $a_3 = X$	$X_0 = \frac{T_0^{b_1}/H_0 - b_2}{b_3 + T_0^{b_1}}$	$H = \frac{T^{b_1}}{b_2 + b_3 X_0 + X_0 T^{b_1}}$ (F13)
Sloboda: $H = a_1 \exp\left(-a_2 \exp\left(\frac{a_3}{(a_4 - 1)^{(a_4 - 1)}}\right)\right)$	$a_2 = X$	$X_0 = -\frac{\ln(H_0/b_1)}{\exp\left(\frac{b_2}{(b_3 - 1)T_0^{(b_3 - 1)}}\right)}$	$H = b_1 \left(\frac{H_0}{b_1}\right)^{\exp\left(\frac{b_2}{(b_3 - 1)T_0^{(b_3 - 1)}} - \frac{b_2}{(b_3 - 1)T_0^{(b_3 - 1)}}\right)}$ (F14)
Strand: $H = \left(\frac{T}{a_1 + a_2 T}\right)^{a_3}$	$a_1 = X$ $a_2 = b_1 + b_2 X$	$X_0 = \frac{T_0\left(H_0\left(\frac{1}{b_3} - b_1\right)\right)}{1} + b_2 T_0$	$H = \left(\frac{T}{X_0 + T(b_1 + b_2 X_0)}\right)^{b_3}$ (F15)

Note: H, S (fixed-base-age SI), T and a_1, a_2, \dots, a_n are parameters in base models; b_1, b_2, \dots, b_n are parameters in GADA models; H_0 and H are heights (in m) at age T_0 and T(in years), respectively; X_0 is the solution of X for initial height and age.

In the general implicit form $H = f(T, T_0, H_0, b_1, b_2, \dots, b_n)$, which is the same for all GADA equations, H_0 is an observed height at the observed age T_0 , while H is a predicted height at index age T . H is a local parameter, which is estimated using GADA dynamic equations (Liziniewicz *et al.* 2016). All parameters and equations used to estimate them are presented in Table 2. Base models, from which the relevant dynamic site equations are derived, are represented in the first column. Dynamic site equations, presented in column 4, are the equations used in the construction of height development models and estimation of their parameters. In case, dynamic site equation consist of theoretical variable X , dynamic equation must be supplemented by the solution of it (column 3).

2.5.2 Diameter model

A function for estimating diameter at the age of 15 years was developed using multiple linear regression analysis. Linear model was applied on the following function:

$$\ln d = f(h, \ln h, H_{gv}, \ln H_{gv}, H_{sum}), \quad (2)$$

where $\ln d$ is a natural logarithm of diameter in cm, h is height, $\ln h$ is natural logarithm of height in m, H_{gv} is basal area weighted mean height, $\ln H_{gv}$ is natural logarithm of H_{gv} , H_{sum} is sum of heights of trees larger than the subject tree. Values of h and $\ln h$ describe each tree individually, while H_{gv} , $\ln H_{gv}$, H_{sum} are estimated on a plot level. Basal area weighted mean height (Lorey's mean height) is introduced because it is more stable compared to the arithmetic mean height and it allows the larger trees to contribute more to the mean. Whereas, H_{sum} is a distance-independent competition index, which describes the intensity of competition between a subject tree and the neighbouring competitors within a plot. H_{sum}_i is calculated in the following way:

$$H_{sum}_i = \sum h_j, \quad (3)$$

when $h_j > h_i$, where h_i is the height of the subject tree and h_j is height of the neighbouring competitor

2.6 Parameter estimation and other computations

Parameter values for all GADA models or equations were estimated with non-linear least-square regression using R functions *nlrob* of package 'robustbase', *nlsLM* of package 'minpack.lm' and *nls* function which is a built-in function in R. In order to achieve a better fit, some of the models were tested with two non-linear fitting functions. All the parameters, both site-specific and global, were estimated simultaneously. Diameter model was estimated using linear regression model *lm*. Other computations, such as evaluation of the models, as well as visual display of the results was performed using R (version 3.5.1).

2.7 Model evaluation

The models developed in this study were evaluated using prediction statistics, graphs of residuals and prediction errors. Height prediction errors were determined by comparing the actual height measurements with the values estimated by models using measured data: models were used to estimate height (H) for every tree at the age of 10 and at the age of 15, if such

records existed. As input data, starting height (H_0) of the respective trees at different index ages was used, e.g. for estimation of height (H) for a tree at the age of 15, starting height (H_0) at different ages ($T_0 = 5, 6, 7, 8, 9, 10, 11, 12, 13, 14$) was used. Statistical accuracy of the models was evaluated by residual analysis using mean prediction error (MPE), standard deviation (SD) and root mean square error (RMSE). In addition, relative quality of the models was determined by Akaike information criterion (AIC) using the built-in AIC function in R.

2.8 Simulations of the further development of the stands

In order to be able to use stand-level management simulator - StandWise and its underlying models for forecasting further development of the stands in Latvian conditions, different variables describing site conditions, such as altitude, latitude, soil moisture, soil texture, vegetation type, had to be specified by approximation based on the location of the study sites. Subsequently, data consisting of tree heights, diameters and site descriptive values were imported into StandWise. Since most of the stands had already reached the age of 15 years, models developed in this study were only used to estimate height and diameter of stands 21, 219 and 168, which were 13, 13 and 14 years old respectively at the time of measurements. With the given starting values, current growth and yield of the stands was estimated at the age of 15 years.

Table 3. Stand data (Forest data)

Variable	Basal area	Dgv	Dominant Height	Hgv	SIH estimated	Stand age	Starting values	Stems	Volume
Unit	m ² ha ⁻¹	cm	m	m	m	yrs	h&d	trees ha ⁻¹	m ³ ha ⁻¹
Stand ID									
55	16.99	11.9	9.07	8.02	35.7	15	meas.	1840	83.6
114	18.8	13.4	10.35	9.4	36.43	15	meas.	1500	91.7
179	16.55	13.3	10.47	9.3	35.77	15	meas.	1720	80.0
119	18.34	11.1	9.73	8.5	36.69	15	meas.	2380	83.6
512	17.55	12.6	10.04	9	35.59	15	meas.	1740	82.8
219	14.39	10.2	8.52	7.6	36.24	15	est.	2020	58.7
216	16.45	9.8	9.08	7.8	36.16	15	meas.	3020	69.6
217	13.84	10.1	8.12	7.1	34.9	15	meas.	2300	53.2
218	16.07	10.3	9.1	7.9	36.15	15	meas.	2700	68.0
21	15.39	9.7	8.37	7.4	36.16	15	est.	2400	61.4
168	12.91	10.3	8.04	7.2	34.92	15	est.	1940	49.7
1214	12.99	11.4	8.72	7.8	35	15	meas.	1720	53.7

Note: Data in this table is based on fully stocked sample plots; **Starting values:** *meas.* is measured and *est.* is estimated; SIH (H100) - calculated based on site factors for Norway spruce (Hägglund and Lundmark 1977)

Subsequently, the course of growth of each stand was simulated by applying a standard management regime: 2 – 3 thinnings from below (relative diameter ratio – 0.9) with an intensity of 30 – 35 %. Simulation results were estimated and demonstrated for every 5 year period in the form of a new status for the stand, timber production and economy, represented with previously selected stand variables. Financial value of the stands was displayed by *Total Cost*

and *Net Revenue*. In order to make the results more admissible, default timber price list was replaced by a timber pricelist based on situation currently existing in Latvian roundwood market (Table 4). In addition, bucking specifics, i.e. minimum and maximum length and diameter of sawlogs and pulpwood were adjusted based on the provided pricelist (Table 4). The Costs of different management operations such as regeneration, cleaning, thinning largely coincided with the costs in Latvia (Table 5). More specific indicators such as technological parameters (machine related) were assumed to be similar in Sweden and Latvia, therefore they were not modified.

Table 4. StoraEnso timber pricelist for Norway spruce in Latvia, 2019 (€m⁻³)

Length (m) Diam. (cm)	3.6	3.9	4.2	4.5	4.8	5.1	5.4	5.7	6.0
Roundwood									
9 – 11.9	53	53	53	53	53	50	50	50	50
12 – 13.9	58	58	58	58	58	55	55	55	55
14 – 17.9	69	69	69	69	69	69	69	69	69
18 – 23.9	75	75	77	77	80	80	80	70	70
24 – 27.9	75	75	77	77	80	80	80	70	70
28 <	70	70	70	70	70	70	70	65	65
Pulpwood	3.0								
6 – 70	42								

Table 5. List of adjusted costs used in the simulations (€)

Regeneration		Cleaning	Thinning			Final felling	
Soil preparation (€ha ⁻¹)	Cost per sapling (€ sapling ⁻¹)	Cleaning cost per ha (€ha ⁻¹)	Harvester hour cost (€G15-hour ⁻¹)	Understory cleaning (€ha ⁻¹)	Forwarder hour cost (€G15-hour ⁻¹)	Harvester hour cost (€G15-hour ⁻¹)	Forwarder hour cost (€G15-hour ⁻¹)
112	0.18	122	94	112	65	103	75

Note: Cost table obtained from CSB of Latvia

Following the simulations, maximum mean annual increment (MAI_{max}) was estimated to determine the age when MAI reaches its climax. As economic indicators, net present value (NPV) and land expectation value (LEV) was estimated for every stand using an interest rate of 2.5 %. Interest rate was assumed to be the same as in Sweden.

$$NPV = \sum_{t=0}^n \left(\frac{R_t}{(1+i)^t} \right) \quad (4)$$

$$LEV = NPV \frac{(1+i)^u}{(1+i)^u - 1}, \quad (5)$$

where R_t is net cash inflow-outflow during a single period t , i is discount rate, n is number of time periods, u is rotation age.

Furthermore, optimal rotation age was determined by estimating land expectation value (LEV) for every stand. In order to ascertain the age at which LEV reached its maximum value, several simulations were performed, every time indicating different age of final felling. Subsequently, LEV was estimated for each scenario and then plotted against the corresponding age. Thereupon, a polynomial regression model of second order was fitted on the curve providing a function, which then was used to estimate LEV_{max} . MAI_{max} was estimated following the same sequence of actions.

3. Results

3.1 Height development models

Out of fifteen tested GADA equations, those based on base equations of exponential form showed the best fit. The parameter estimates for each model and their fit and prediction statistics are summarized in Table 6. All parameters, except parameter b_2 and b_3 of model F13, were found to be significant at 1% level. Models showed different goodness-of-fit statistics, varying from very good fit, shown by models developed using equations F01, F02 and F14, to mediocre and even rather poor fit. Based on the graphical appearance of models (Appendix 1.), most of the models showed poor ability to follow and encompass the actual growth pattern of measured trees. Models F02; F03; F05; F08 and F14 had the best visual conformity with the measured data, but models F03 and F14 were identified as superior ones. Both, model F03 (developed using Chapman-Richards base model) and F14 (developed using Sloboda base model) showed very good fit statistics and had the best prediction statistics, i.e. Chapman-Richards model and Sloboda model had the smallest mean prediction error (MPE) and smallest standard deviation (σ) within the predicted values, when predicting height at both 15 (Fig. 7) and 10 years (Fig. 8) of age.

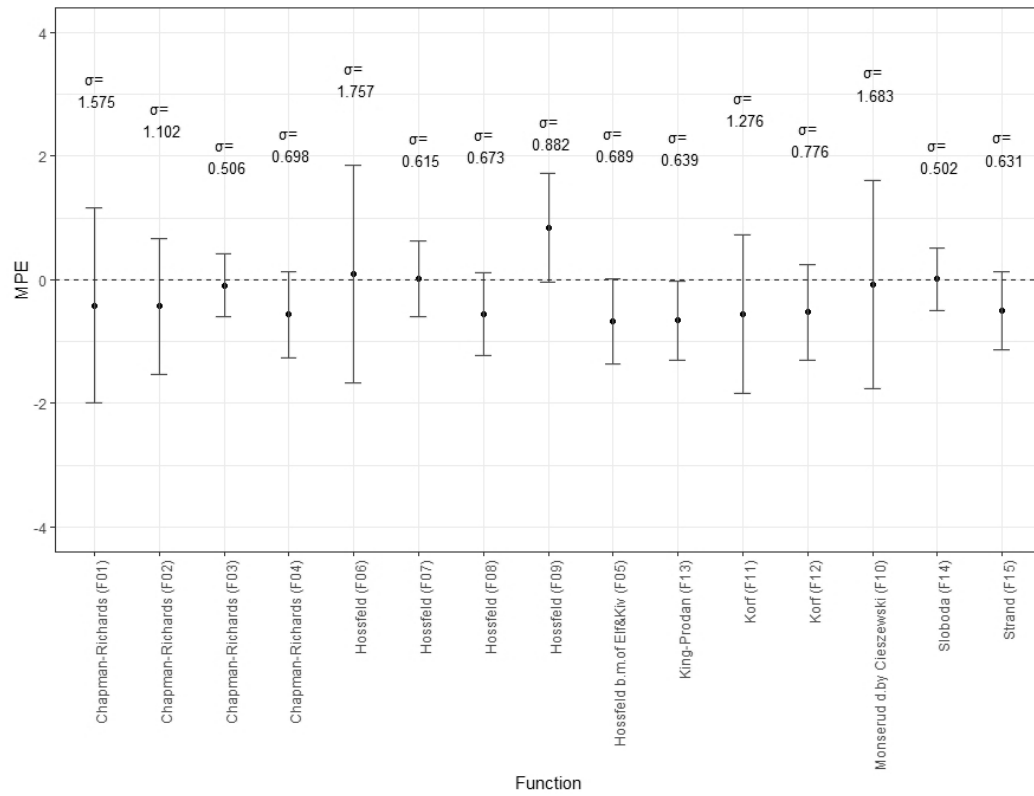


Figure 7. Mean prediction error (MPE) for height predictions at the age of 15 years.

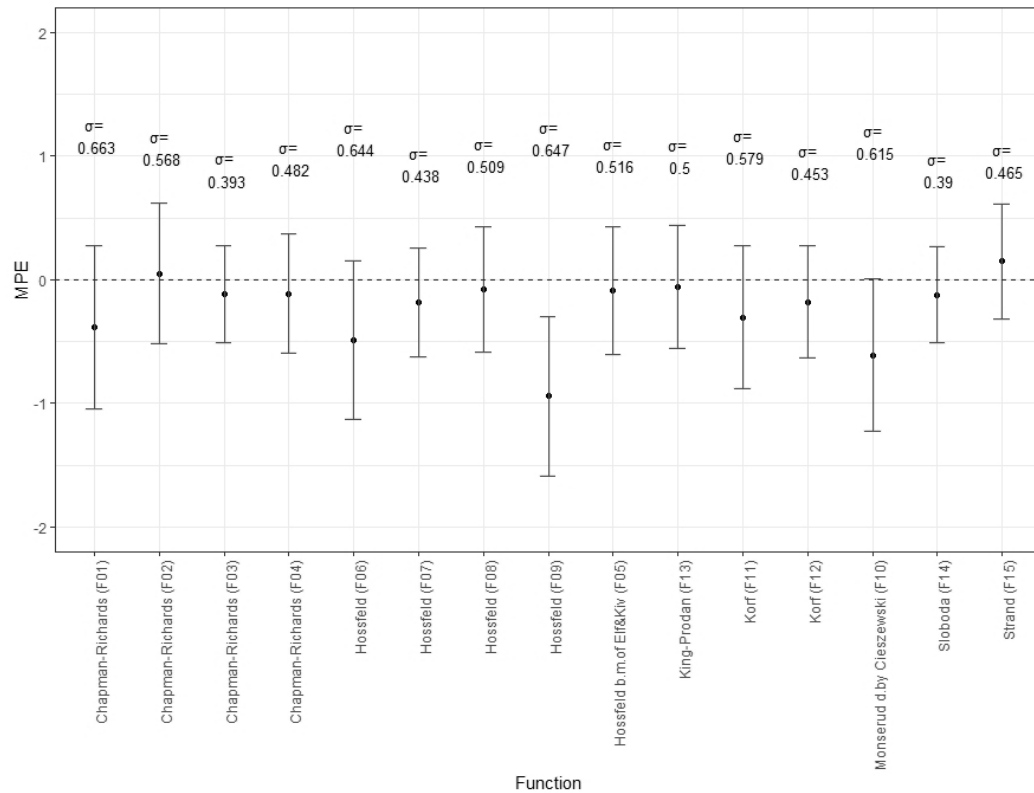


Figure 8. Mean prediction error (MPE) for height predictions at the age of 10 years.

Considering the superior performance of models F03 and F14 in every aspect evaluated, the following results will focus on only these two models. Both models outperformed other candidate models when their accuracy to predict the height of individual trees was tested. All models were tested by their ability to predict height at the age of 10 and at the age of 15 years using different starting heights at different reference ages. For most of the models, including Chapman-Richards and Sloboda model, prediction errors increased with an increasing difference in age between the starting height and predicted height, i.e. the younger the tree, the larger the error when predicting its height at later age. Chapman-Richards and Sloboda model (Fig. 9 & 10) both had the largest MPE (-0.345 m and -0.232 m respectively) when predicting height from 6 years of age. Contrary to Chapman-Richards model, Sloboda model showed higher accuracy in predicting height at the age of 15 years. As the age difference between the starting height and predicted height decreased, Chapman-Richards model showed more stability and thus higher precision compared to Sloboda model which showed more fluctuating predictions.

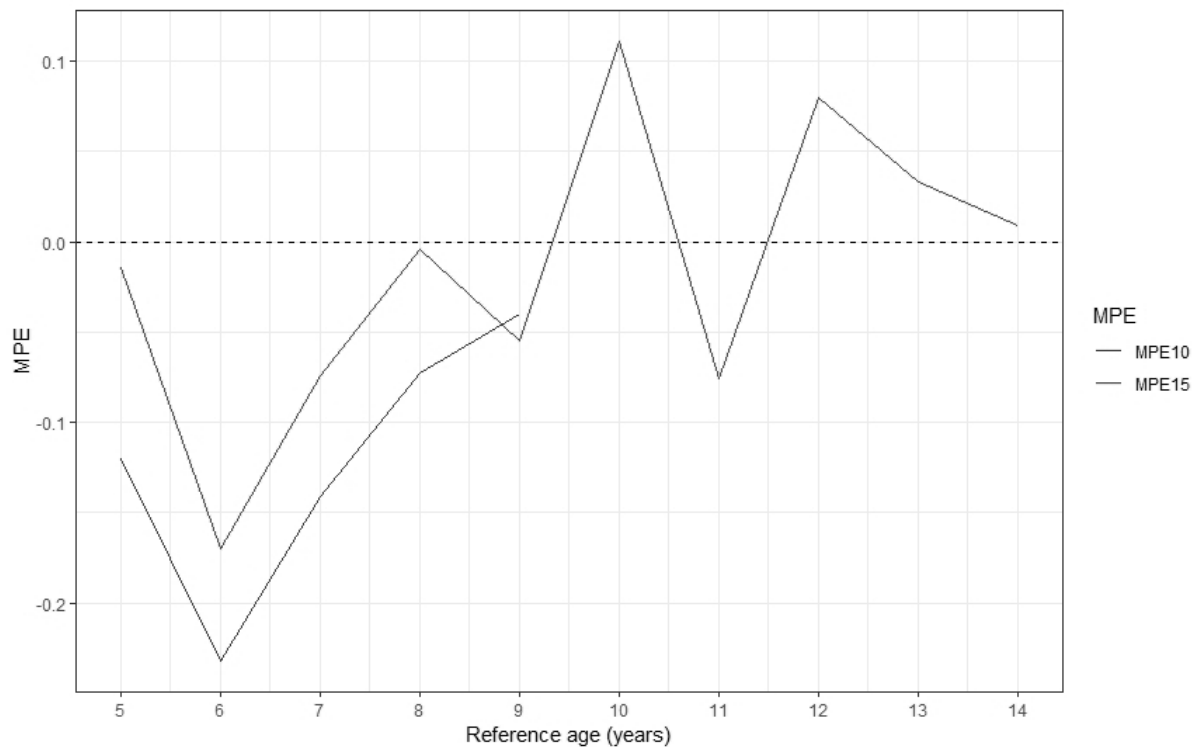


Figure 9. MPE's for Sloboda height growth model.

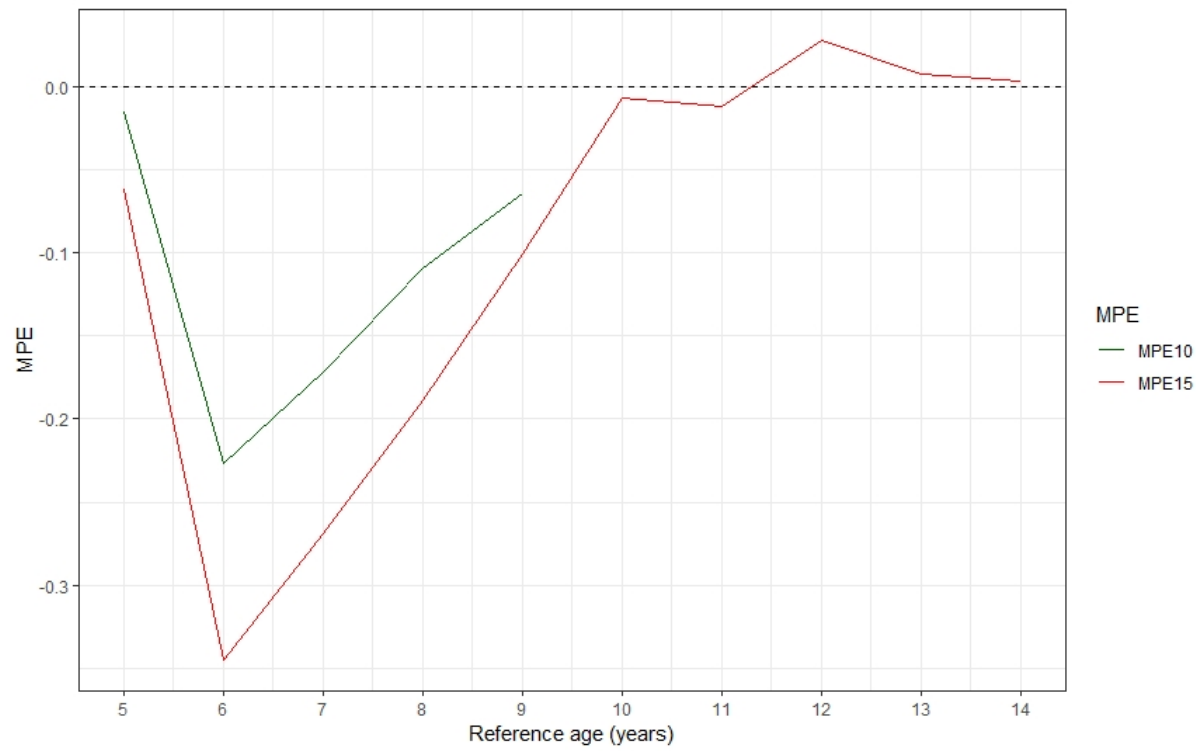


Figure 10. MPE's for Chapman-Richards height growth model.

Table 6. Parameter estimates and fit statistics of models used in this study

Model	Fit statistics					Prediction statistics						
	Param.	Est.	SE	t	p > t	MPE10	MPE15	SD10	SD15	RMSE10	RMSE15	AIC
F01	b2	0.0644	0.0013	48.31	$2*10^{-16}$	-0.383	-0.42	0.663	1.575	0.7650	1.6296	35 583
	b3	2.5979	0.0164	158.18	$2*10^{-16}$							
F02	b1	14.7232	0.0897	164.0	$2*10^{-16}$	0.049	-0.432	0.482	0.698	0.4950	0.8939	24 398
	b3	3.9272	0.0198	198.2	$2*10^{-16}$							
F03	b1	19.23	0.1368	140.6	$2*10^{-16}$	-0.117	-0.095	0.393	0.506	0.4099	0.5148	14 208
	b2	0.1062	$7.421*10^{-4}$	143.1	$2*10^{-16}$							
F04	b1	0.1646	0.0014	109.90	$2*10^{-16}$	-0.114	-0.559	0.568	1.102	0.5695	1.1828	28 170
	b2	7.563	0.0704	107.37	$2*10^{-16}$							
F05	b3	-0.1857	0.0022	-81.72	$2*10^{-16}$							
	b2	-2.825	$7.606*10^{-3}$	-371.4	$2*10^{-16}$	-0.089	-0.676	0.516	0.689	0.5231	0.9652	33 723
F06	beta	$1.191*10^{-3}$	8.661	137.5	$2*10^{-16}$							
	b1	$2.392*10^{-7}$	$4.466*10^{-4}$	535.5	$2*10^{-16}$	-0.488	0.094	0.644	1.757	0.8243	1.7590	47 714
F07	b2	$3.119*10^{-7}$	$6.263*10^{-4}$	498.0	$2*10^{-16}$							
	b3	1.918	$2.202*10^{-3}$	871.3	$2*10^{-16}$							
F08	b1	10.8145	0.0357	302.81	$2*10^{-16}$	-0.183	0.017	0.438	0.615	0.4744	0.6248	17 264
	b2	124.6595	2.8380	43.92	$2*10^{-16}$							
F09	b3	-2.5256	0.0069	-361.2	$2*10^{-16}$							
	b1	14.1449	0.0743	190.2	$2*10^{-16}$	-0.077	-0.557	0.509	0.673	0.5143	0.8864	24 215
F10	b3	2.8098	0.0068	410.7	$2*10^{-16}$							
	b1	0.09443	$5.434*10^{-4}$	173.8	$2*10^{-16}$	-0.941	0.845	0.647	0.882	1.1418	1.0851	40 901
F11	b2	-0.06473	$9.469*10^{-5}$	-683.6	$2*10^{-16}$							
	b1	$9.655*10^{-3}$	$1.435*10^{-3}$	6.73	$1.76*10^{-11}$	-0.611	-0.087	0.615	1.683	0.8664	1.6844	47 340
F11	b2	0.9701	$1.629*10^{-3}$	595.63	$2*10^{-16}$							
	b3	1.998	$4.806*10^{-3}$	415.86	$2*10^{-16}$							
F11	y0	$-8.332*10^{-3}$	$4.461*10^{-2}$	-18.68	$2*10^{-16}$							
	b1	0.0697	0.0110	6.326	$2.59*10^{-10}$	-0.303	-0.556	0.579	1.276	0.6536	1.3916	31 984

Table 6 (continued)

Models	Fit statistics					Prediction statistics						
	Param.	Est.	SE	t	p > t	MPE10	MPE15	SD10	SD15	RMSE10	RMSE15	AIC
F12	b2	54.8724	0.7035	77.995	2*10 ⁻¹⁶							
	b3	0.5018	0.0070	70.958	2*10 ⁻¹⁶							
	b1	57.4726	1.2965	44.33	2*10 ⁻¹⁶	-0.179	-0.521	0.453	0.776	0.4867	0.9347	25 565
	b3	0.7004	0.0057	121.99	2*10 ⁻¹⁶							
F13	b1	2.879	7.197*10 ⁻³	400.03	2*10 ⁻¹⁶	-0.059	-0.656	0.5	0.639	0.5030	0.9157	32 219
	b2	-4.511*10 ⁺⁶	2.46*10 ⁺⁸	-0.183	0.854							
	b3	6.002*10 ⁺⁷	3.273*10 ⁺⁸	0.183	0.854							
	b1	54.8724	0.1088	147.534	2*10 ⁻¹⁶	-0.121	0.01	0.390	0.502	0.4085	0.5018	12 180
F14	b2	0.5018	0.0025	68.72	2*10 ⁻¹⁶							
	b3	57.4726	0.0082	4.787	1.71*10 ⁺⁶							
	b1	0.7004	2.095*10 ⁻³	561.63	2*10 ⁻¹⁶	0.148	-0.495	0.465	0.631	0.4878	0.8017	26 707
	b2	2.879	4.471*10 ⁻⁴	-58.22	2*10 ⁻¹⁶							
F15	b3	-4.511*10 ⁺⁶	0.1902	-89.32	2*10 ⁻¹⁶							

Note: **Param.** is parameter, **Est.** is estimated value of the parameter, **SE** is standard error, **MPE** is mean prediction error, **SD** is stadard deviation and **RMSE** is root mean squared error.

3.2 Diameter models

In order to be able to estimate DBH of trees at the age of 15 years, two linear regression models were developed using variables estimated on a plot level. Model parameter estimates, fit and prediction statistics are shown in Table 7. Model dm_1 was constructed using two tree-level parameters (h , lnh) and three plot-level parameters (H_{gv} , lnH_{gv} , H_{sum}). All parameters were found to be significant at 1% level, except parameter H_{gv} , which had a p value of 0.0214. Model dm_2 was constructed using two tree-level parameters (h , lnh) and only one plot-level parameter – lnH_{gv} , but all parameters were found to be significant at 1% level. The visual appearance of models is shown in Appendix 2.

Table 7. Parameter estimates and fit statistics of diameter models developed in this study

Model	Fit statistics					Pred.stat.		
	Param.	Est.	SE	t	p > t	R ²	R ² _{adj}	RMSE
dm_1	Intercept	2.148	0.3323	6.466	$1.44 \cdot 10^{-16}$	0.9411	0.9408	0.8224
	h	0.1278	0.0131	9.798	$2 \cdot 10^{-16}$			
	lnh	0.6998	0.069	10.137	$2 \cdot 10^{-16}$			
	H_{gv}	0.09536	0.0414	2.304	0.0214			
	lnH_{gv}	-1.424	0.3207	-4.442	$9.67 \cdot 10^{-6}$			
	H_{sum}	-0.00129	$8.671 \cdot 10^{-5}$	-14.871	$2 \cdot 10^{-16}$			
dm_2	Intercept	2.19241	0.096	22.839	$2 \cdot 10^{-16}$	0.9306	0.9305	0.9541
	h	0.23915	0.011	21.207	$2 \cdot 10^{-16}$			
	lnh	0.29279	0.06663	4.395	$1.2 \cdot 10^{-5}$			
	lnH_{gv}	-1.14139	0.03507	-32.547	$2 \cdot 10^{-16}$			

Models showed very similar results when evaluated by their fit on the data and predicting ability. In the fitting phase, model dm_1 explained more than 94 % of the total variance, while model dm_2 explained slightly over 93%. In addition, root mean squared error (RMSE) was significantly smaller for model dm_1 compared to model dm_2 .

3.3 Simulations of the further development of the stands

The main, stand descriptive variables are summarized in Table 8. According to SI (Hägglund and Lundmark 1977) estimates, all stands have high growth potential with all stands having SI value no less than 36. The highest SI (exceeding SI 37) was estimated for stands, 119, 21, 216, 218, 219, while the lowest SI was estimated for stands 168 and 217. Accordingly, stands with the highest SI estimates showed the highest mean annual growth. Stands 119, 21 and 216 had the highest MAI_{max} and the highest potential volume production during the rotation. In addition, optimal rotation age (economic maturity age) was determined by calculating land expectation value (LEV).

Table 8. Heureka simulation results and estimates of optimal rotation age using 2.5 % interest rate

Stand ID	FT	Site index	MAI _{max} (m ³ ha ⁻¹ year ⁻¹)	Age (MAI _{max}) (years)	Optimal FF age (years)	MAI at final felling age (m ³ ha ⁻¹ year ⁻¹)	LEV (€)
55	Vr	36.5	16.1	52	44	15.7	16 172
114	Vr	36.9	16.4	51	41	15.8	17 255
179	Dm	36.5	15.5	53	42	14.9	15 434
119	Vr	37.9	17.6	51	43	17.1	17 516
512	Vr	36.9	16.5	52	42	15.7	16 650
219	Vr	37.2	16.9	60	46	15.9	15 639
216	Vr	37.6	17	52	45	16.6	16 087
217	Vr	36.3	15.3	57	48	14.8	14 282
218	Vr	37.2	16.8	53	44	16.2	15 907
21	Vr	37.3	17.6	49	42	17.1	17 616
168	Dm	36.1	15.3	58	45	14.5	14 871
1214	Vr	36.5	14.7	57	46	14	14 643

Note: SI (H100) - calculated based on site factors for Norway spruce (Hägglund and Lundmark 1977)

Estimates of optimal rotation age showed that all stands reach their economic maturity 7 – 14 years before MAI reaches its climax, indicating that in case stands were harvested at their economic maturity age, it would not maximize long-term sustained yield. Based on the conditions specified in this study, the highest LEV values were calculated for stands 21, 119 and 114 and therefore to maximize financial outcome, these stands should be harvested relatively early: at the age of 42, 43 and 41 respectively. On the contrary, the smallest LEV was estimated for stands 168, 1214 and 217 and these stands should be harvested relatively late, both when evaluated with long-term production and economy. However, MAI_{max} and LEV are inconsistent variables as their values depend on several factors such as site quality and potential timber production, management and market situation (for LEV), therefore these values should be interpreted with precaution.

4. Discussion

4.1 Height development model

Due to the rapid growth, currently available models are unable to predict growth of Norway spruce with sufficient accuracy, therefore the objective was to develop new models, which could be used to address forest management related matters. Different forms of height development models exist, varying in complexity and performance. For quite some time now, difference equation method (GADA) has been recognised as advantageous and has been widely used in development of dominant height growth models (Hann & Scrivani, 1986; Fontes *et al.*, 2003; Weiskittel *et al.*, 2009; Nord-Larsen *et al.*, 2009; Sharma *et al.*, 2011; Liziniewicz *et al.*, 2016; Donis, 2018). Based on the knowledge acquired in previous studies, fifteen different GADA equations were selected and tested in this study.

Results showed varying goodness of fit between the tested equations. The best performance was demonstrated by models of exponential form – the Chapman-Richards and Sloboda model. Both height growth models had better prediction statistics than other models. Chapman-Richards model had a MPE of -0,117 m and -0,095 m, predicting height at the age of 10 and 15 years respectively, while Sloboda model showed a MPE of -0,121 m and 0,01 m, predicting height at the same ages.

Based on model evaluation, no clear preference of which model is better can be made. Both models have good fit and prediction statistics and they both represent parsimonious, dynamic height equations, forming polymorphic models with several asymptotes. However, Chapman-Richards model appears to be more realistic, i.e. modelled curves better encompass the actual height development of measured trees, thus having a better conformity with the data. In addition, residual analysis showed that residual pattern of Sloboda model is more heteroscedastic, i.e. residuals are not evenly distributed throughout the predicting range and that the variance along the residuals is non-constant. While none of the models really showed a homoscedastic pattern of residuals, Chapman-Richards model showed a slightly better, more evenly distributed pattern (Appendix 3.). Heteroscedastic pattern of residuals may be explained with an independent variable, in this case starting or input height, which causes error variance to be larger when using height at earlier ages as input values. Both, Chapman-Richards model and Sloboda model affirm the above said, as they show larger error variance at smaller starting heights, indicating to more imprecise predictions when predicting future height at younger ages (Appendix 3.). Considering the results of model evaluation, Chapman-Richards model shows better overall performance, therefore the author finds Chapman-Richards model as the most suitable and recommends the use of this model for further needs.

There are two main reasons behind higher MPE's when predicting height at a younger age. First of all, the accuracy of estimated height may decrease due to accumulation of errors as the forecasting time period increases, i.e. predicting height of a tree after 10 years may produce a larger error than predicting tree height after one year. Secondly, due to the stressful conditions during the establishment phase, e.g. limited availability of water and nutrients caused by competing vegetation, damages caused by pine weevil, frost or browsing, seedling and young tree growth is often challenged. Therefore, course of development of trees at such a young age is very difficult to predict, because it has little to do with their future growth. In order to be able to accurately predict tree development from such a young age, complex

models would be needed, to explain the impact of various factors on tree development. However, that might be a difficult task, due to a large number of confounding factors affecting tree development, as well as it might be difficult to measure the potential presence of each factor and thus to explain the variation of tree height.

Certainly, the model developed in this study is not faultless and its accuracy could be improved in different ways. When it comes to this study, larger dataset, i.e. data from stands scattered over a wider area representing different fertility sites would presumably increase the accuracy of the model as well as make it more reliable when applied to other regions. According to Weiskittel *et al.*, 2011, size, alongside with type and quality of the data have important implications for the modelling effort. Although, modelling dataset could potentially be supplemented with data from different regions of the country, it has to be reminded that tree-level models are expensive to develop, which is mainly due to time and labour-consuming nature of destructive sampling - necessary to obtain a satisfying amount and type of data. Using National Forest Inventory data in development of growth models could solve this problem. Thus far, in Latvia NFI data has been used only in few studies (Donis *et al.*, 2015; Donis & Šņepsts, 2015; Šņepsts & Donis, 2017; Donis, 2016, 2017, 2018), what could be explained with the fact that NFI in Latvia was started quite late – 2004, compared to countries such as Sweden and Finland. Nevertheless, Donis (2016) considers that most variables needed to develop individual tree-level models are found within the NFI database, directly or after calculations. However, data describing management activities before 10 years might not always be available.

Another way how to improve the precision of the model, without extensive and expensive collection of data, would be by more thorough model evaluation, i.e. benchmarking of the model. Benchmarking can be used to obtain quantitative assessment of the model performance. However, benchmarking requires independent data of sufficient quality, sufficient size and representative of full range of modelled population (Weiskittel *et al.*, 2011). Unfortunately, such independent data was not accessible in this study. In case such data was available and benchmarking revealed certain deficiencies in the model, a re-calibration of the model could be performed by estimating new parameters of the equations or by adjusting predictions using a simple scaling factor.

The growth model developed in this study could face several challenges in distant future. One of the challenges could be maintaining its ability to accurately predict height in a changing climate. Climate change is predicted to have a positive effect on growth and subsequent biomass production for all species common in Latvia (Jansons, 2015) due to increased temperatures and atmospheric CO₂ concentrations as well as longer vegetation periods, which would enable trees to utilize more solar radiation through photosynthesis. Due to potential change in growth patterns, model based on “outdated” growth data might have a problem to predict height of the trees with sufficient accuracy. Secondly, improved tree growth is expected due to active and ongoing tree breeding programs focused on common tree species in Latvia, including Norway spruce (Zeltiņš, 2017). With tree breeding continuously providing new generations of improved material, there might be a need to develop new growth models or refit the existing growth equations on growth data of new generation material (Egbäck, 2016). Some of these shortcomings or potential problems could be solved by developing models that are able to maintain their accuracy and that are adaptable to changing confounding factors such as increased temperature, increased growth

season and changes in tree genetic material. For instance, several climate-sensitive empirical growth and yield models with integrated environmental factors (Trasobares *et al.*, 2016; Zell, 2018) and empirical growth models with incorporated genetic effects of different genetic entries (Gould *et al.*, 2008; Egbäck, 2016) have been developed. Besides statistical modelling approaches, growth and yield of individual trees and stands can be modelled using process-based or hybrid modelling approach. However, these modelling approaches suffer from their own disadvantages: lack of knowledge on tree physiological processes; these models may require data that is not typically available or requires expensive, labour-intensive data collection methods; these models are not error-free and show relatively small increase in accuracy compared to statistical models.

Although, the height growth model developed in this study has certain disadvantages, it is a reliable model with an ability to accurately predict height, provided it is applied within its scope.

4.2 Diameter models

Secondary objective of this study was to develop models for diameter at breast-height (DBH). Diameter models were developed based on the fundamental relationship between tree height and DBH, which is often used to characterize forest stands. Two models were tested: 1) dm_1 – a six-parameter function (Const., h , $\ln h$, H_{gv} , $\ln H_{gv}$ and H_{sum}) and 2) dm_2 – a four-parameter function (Const., h , $\ln h$, $\ln H_{gv}$).

According to results, both models performed very good when fitted on the data. In addition, residual analysis (Appendix 4.) showed no apparent differences between the two models that would favour or disfavour either model. Following the statistical and graphical evaluation of both models, it can be inferred that addition of complex variable H_{sum} to function of model dm_1 contributes relatively slightly to its accuracy. However, given the slightly better fit and predicting ability of model dm_1 , it is identified as the best from two candidate models and therefore it is recommended to use this model for the estimation of DBH of Norway spruce at the age of 15 years.

With the development of diameter model, it is now possible to model development of planted Norway spruce stands from 5 years of age. Using the Chapman-Richards height development function constructed in this study, height of Norway spruce can be estimated up to 15 years of age, whereas diameters can be estimated using diameter function of model dm_1 . Trees with estimated height and diameter can then be imported in simulation systems such as Heureka-DSS. Consequently, Heureka-DSS could be used to simulate further stand development with a possibility to implement different management activities such as thinning, fertilization and final felling.

4.3 Simulations of the further development of the stands

The last of the objectives pursued in this study was to evaluate the further stand development using stand-level management simulation and visualization tool – StandWise of the Heureka DSS (Wikström *et al.*, 2011). The aim was to determine growth potential, productivity and economic performance of the stands considered in this study by implementing standard management regime.

The results revealed that stands have a very high growth potential as evidenced by their potential volume growth (MAI) over the period of 40 simulated years. There could be

several reasons behind the rapid growth of Norway spruce: high soil fertility, use of genetically improved seedlings, favourable climatic conditions as well as management. This largely coincides with Evans's (2000) findings that growth of Norway spruce is significantly affected by soil fertility, genetics, microclimate and thinning operations (in regards to merchantable timber, not gross production).

The main purpose of cultivating Norway spruce on plantations such as the ones established in Latvia is to produce timber and thus profit or in other words to generate maximum value from resources used as economically efficient as possible. As shown by land expectation value (LEV) estimates, optimal rotation age of stands considered in this study is reached relatively early, i.e. between 41 – 48 years of age. Compared to the minimal felling age of forest stands, which in Latvia for Norway spruce is 81 years, potential felling age for plantations would be almost twice as less. Moreover, according to simulation results, the potential yield at the end of rotation of plantations would match or exceed the yield produced in forest stands at the age of 81 years.

However, the results presented here are based on simulations, and the precision of the results could be called into question for a number of reasons. Simulation system could be one of the reasons. Heureka-DSS consists of models developed in Sweden (e.g. Fahlvik *et al.*, 2014; Wikström *et al.*, 2011), making their applicability rather precarious and increasing the risk of overestimations or underestimations of certain stand variables. In addition, accumulation of errors of independent variables in each subsequent period may have decreased the overall precision of the results, although, that does not coincide with what Fahlvik *et al.* (2010) found by testing the performance of growth models implemented in Heureka. Another, a rather infallible reason for questionable results is the fact that simulations are based on fully-stocked stands. In reality, stands were not fully-stocked as in many of them openings of different size were present, due to mortality of the trees. However, the primary goal of this study was to construct height development models of Norway spruce which required sample plots with sufficient number of trees, therefore, this is not considered as an inaccuracy of this study.

Finally, yet importantly, based on estimated LEV's, stands reach economic maturity relatively early; however LEV estimates are very unsteady economic indicators, because LEV depends on a number of factors such as volume growth, prices of the timber and management costs. High volume growth and high prices for Norway spruce timber throughout the range of diameter classes, probably were the two main reasons for high LEV estimates and thus relatively low economic maturity age for stands considered in this study. Having regard to the fact, that the stands in real life were not fully-stocked as well as the inconstant timber prices and variable management costs, these results should be interpreted with precaution.

5. Conclusions

The best performance among the 15 tested GADA equations was demonstrated by models of exponential form – Chapman-Richards model and Sloboda model. In-depth evaluation of both models revealed that Chapman-Richards model is more realistic compared to Sloboda model, i.e. it showed better conformity with the measured data and more stable predictions with increasing reference age. Chapman-Richards model showed a MPE of -0,117 m and -0,095 m, predicting height of Norway spruce at the age of 10 and 15 years respectively.

The two diameter models developed in this study showed very similar results when evaluated by their fit on the data and predicting ability. In the fitting phase, model dm_1 explained more than 94 % of the total variance, while model dm_2 explained slightly over 93%. However, slightly better results were achieved by six-parameter function of mode dm_1 , i.e., model dm_1 had significantly smaller root mean squared error (RMSE) – 0.8224, compared to model dm_2 .

Simulation of further stand development using Heureka StandWise, showed that stands considered in this study have high growth potential. Mean annual increment (MAI) for these stands varied between $14.7 - 17.6 \text{ m}^3 \text{ ha}^{-1} \text{ year}^{-1}$. According to the estimates of land expectation value (LEV), stands would reach their economic maturity age 7 – 14 years before MAI culminates. The optimal rotation age of the stands varies between 41 – 48 years. However, it has to be noted, that simulations and all calculations were based on fully-stocked stands which does not correspond to the real situation.

In closing, successful development of Norway spruce stands depends to a large extent on robust, well-weighed, well-timed management activities. Stage of development of young stands is particularly important; however, models that would accurately describe development of young stands in Latvia are missing. Models developed in this study can be used as practical tools in management of young Norway spruce stands. With the current set of models, development of planted Norway spruce plantations can be modelled from 5 up to 15 years of age. Accurate estimates of height, for instance, are of high importance when it comes to planning of pre-commercial thinnings. Moreover, tree heights and diameters, estimated by the models, can now be imported in decision support systems such as Heureka. Hence, the forthcoming management operations such as commercial thinnings, can be planned within full rotation projections of the stands.

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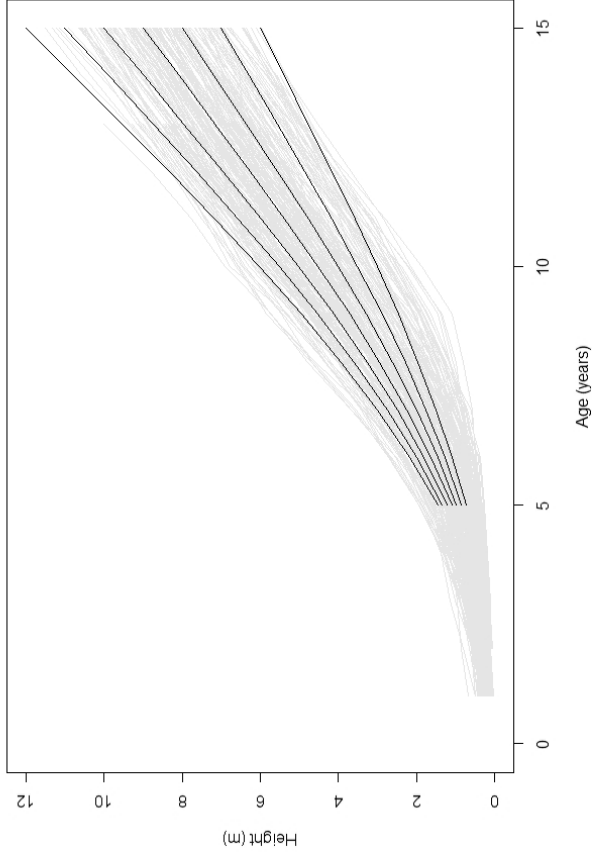
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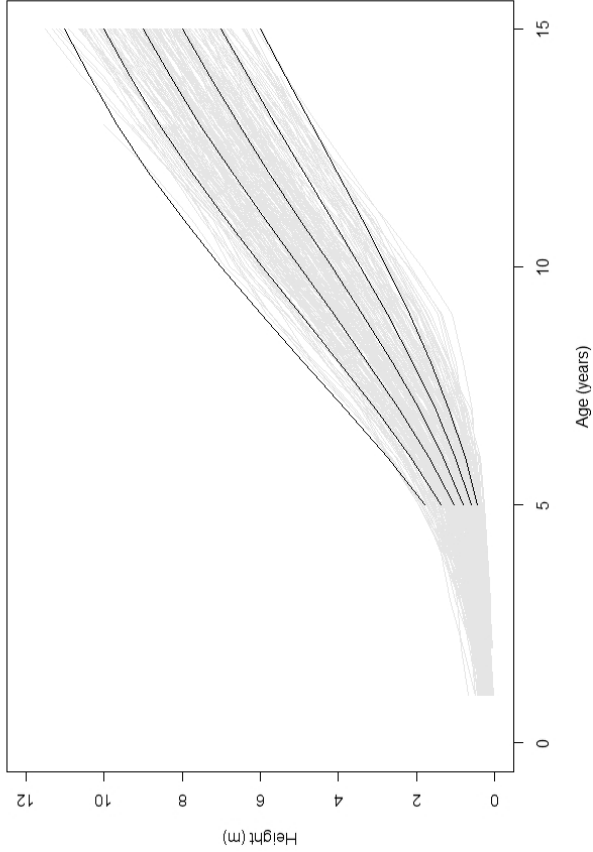
Appendix

Appendix 1. Dominat height growth models

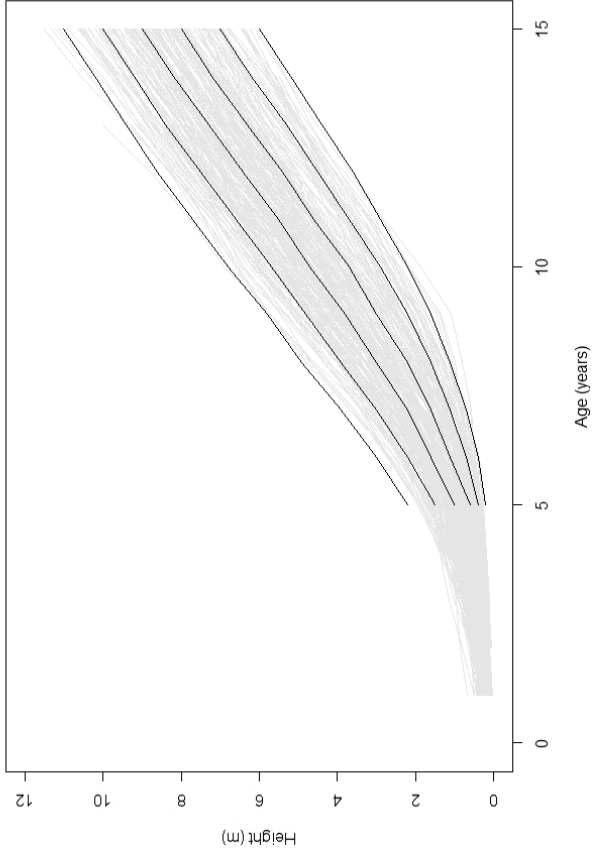
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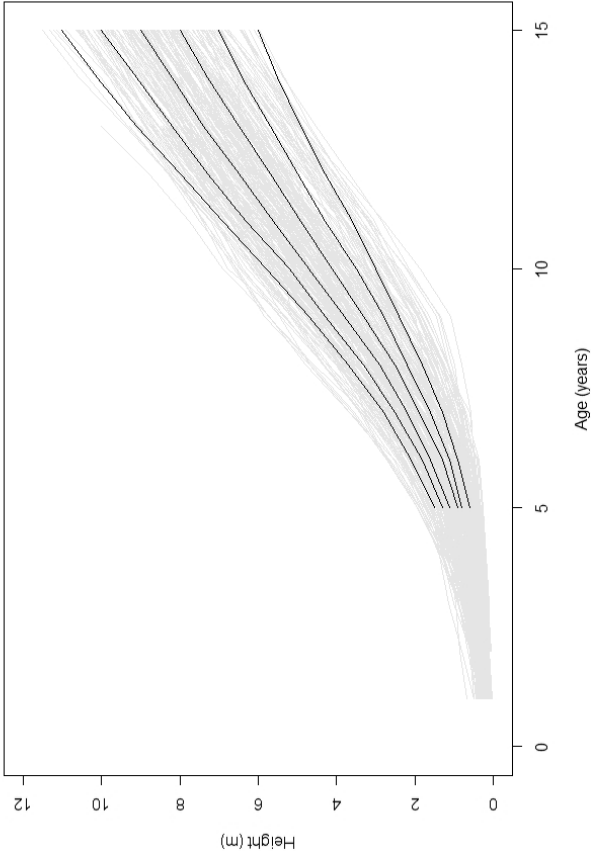
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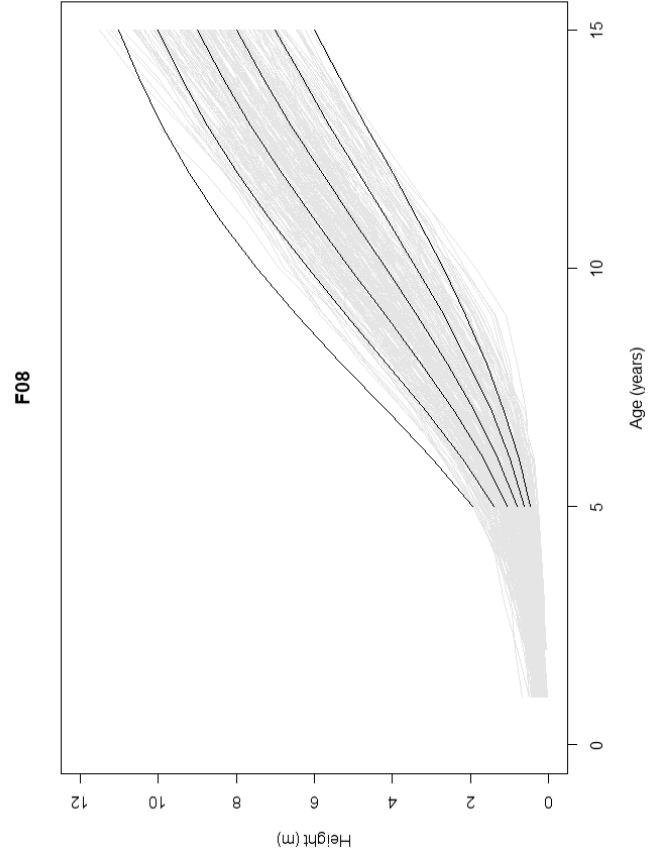
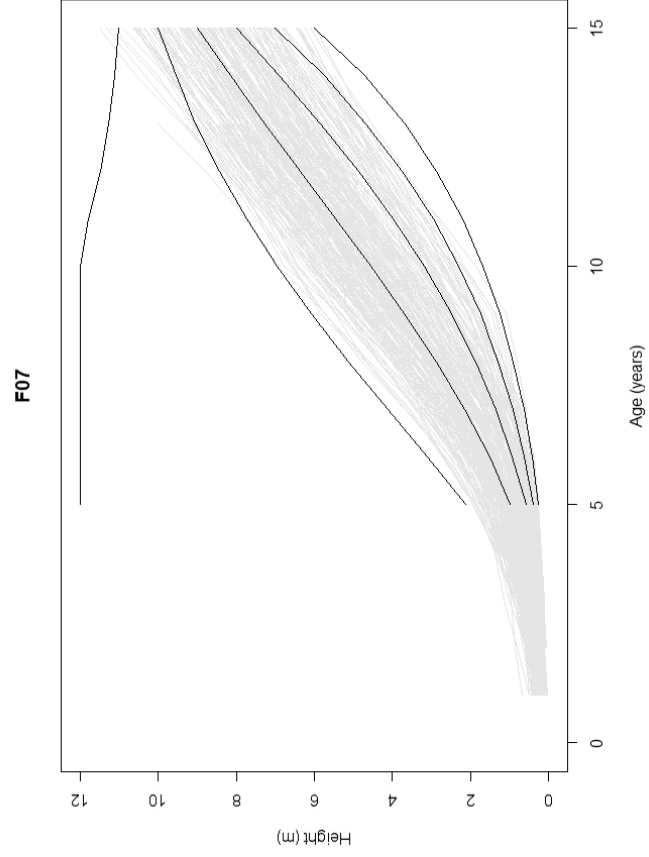
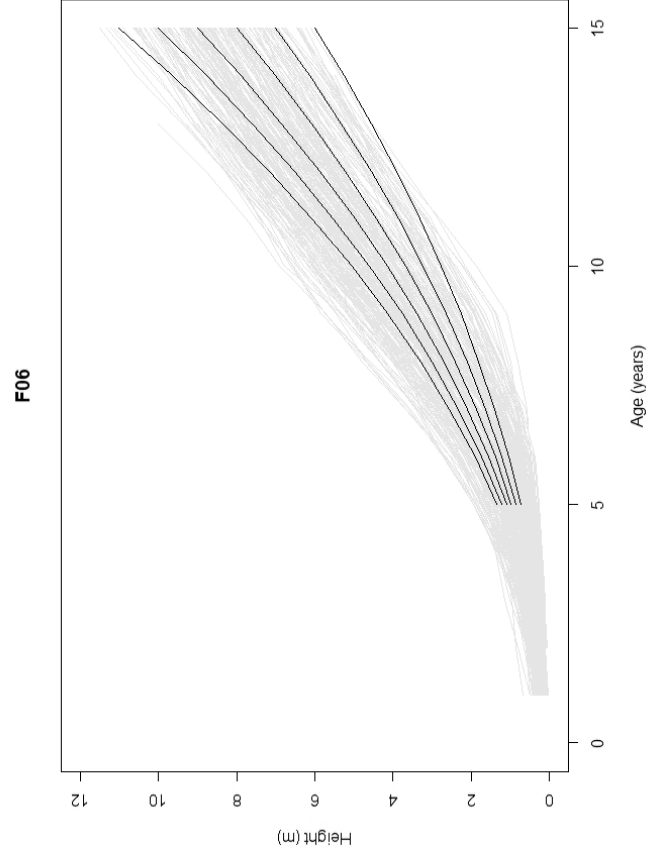
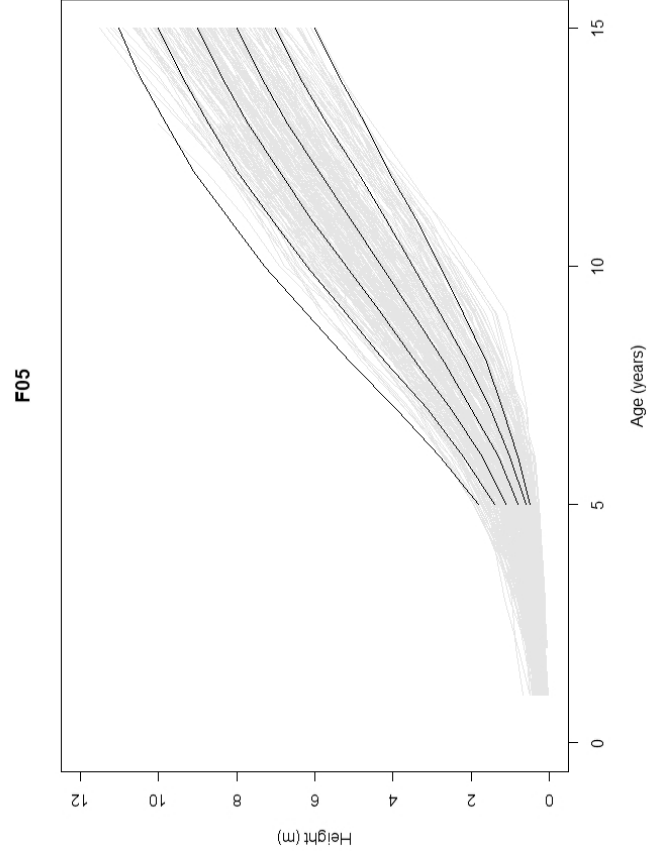


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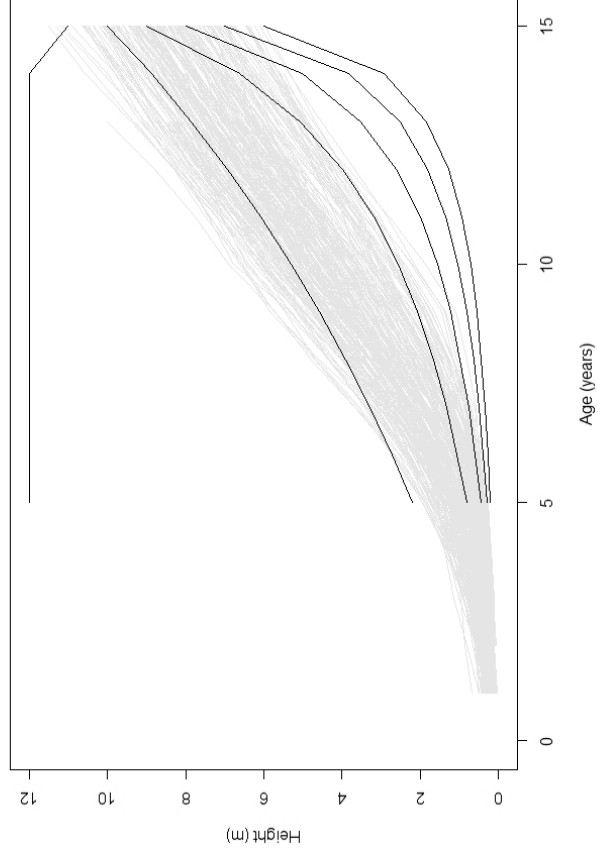


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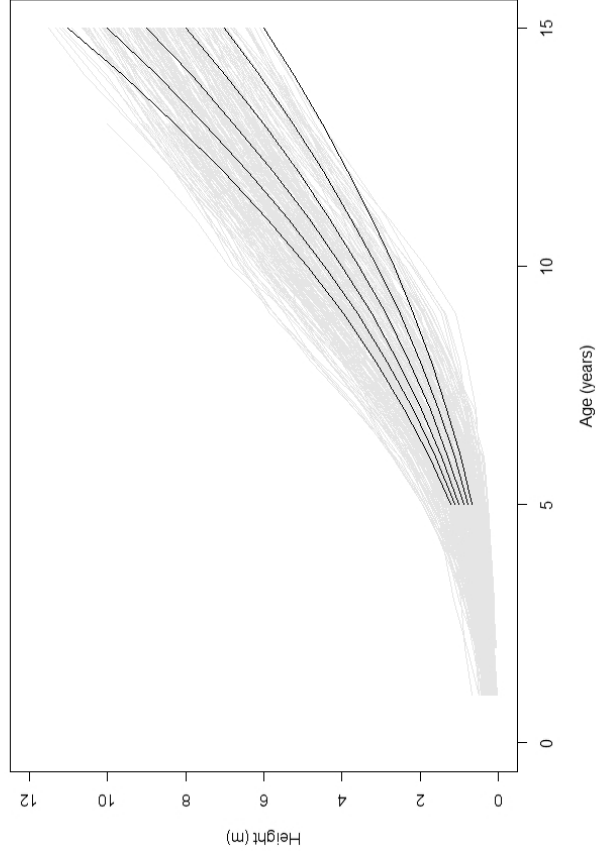




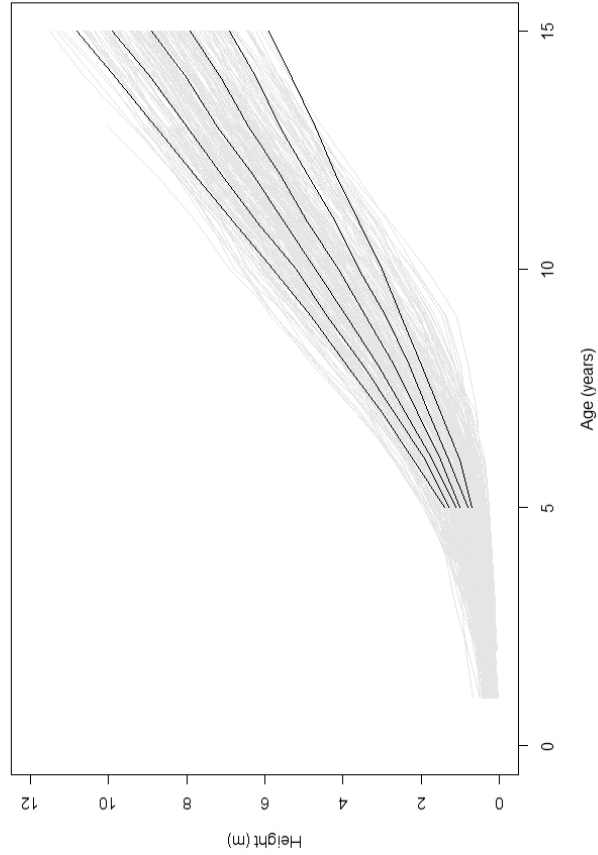
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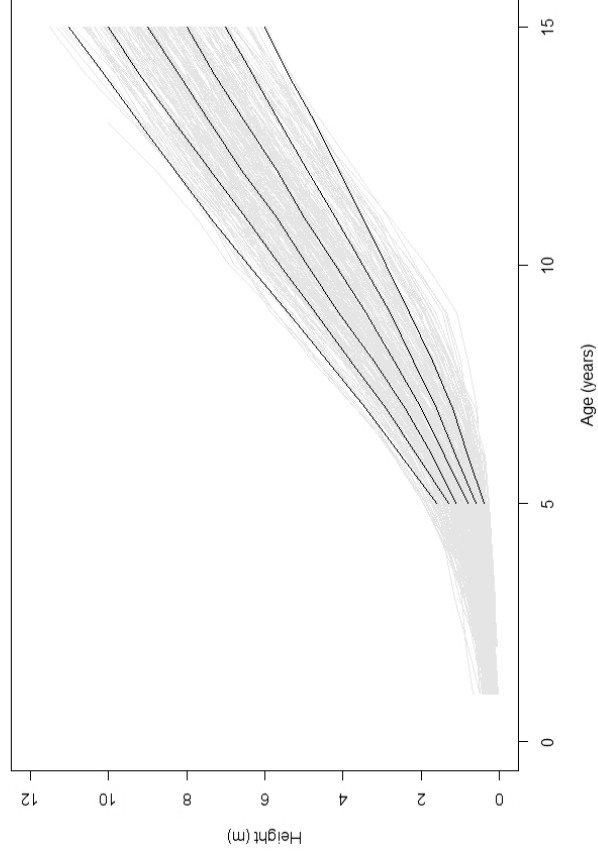
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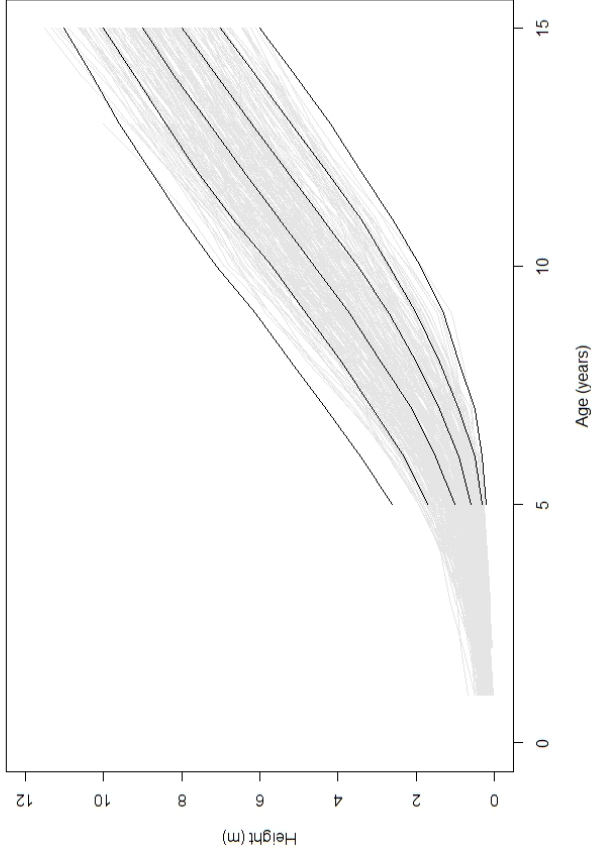
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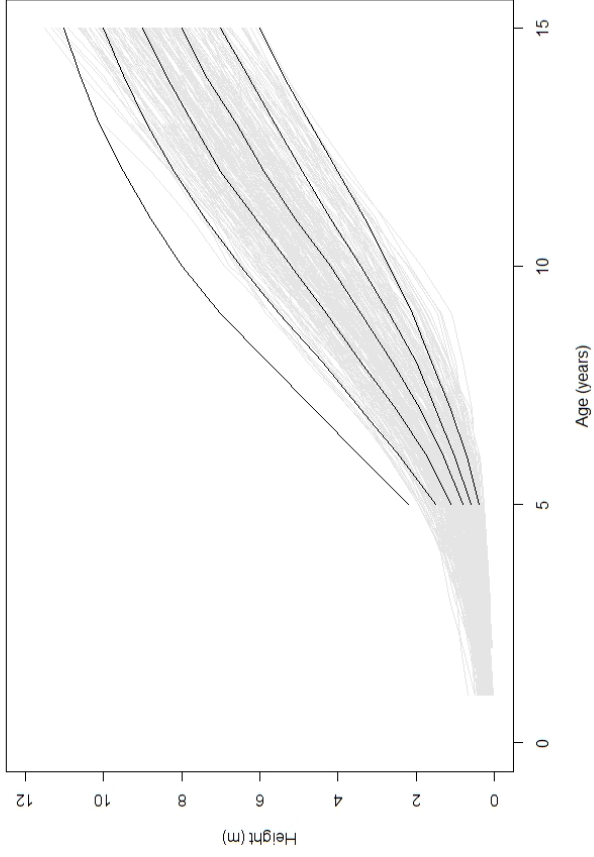
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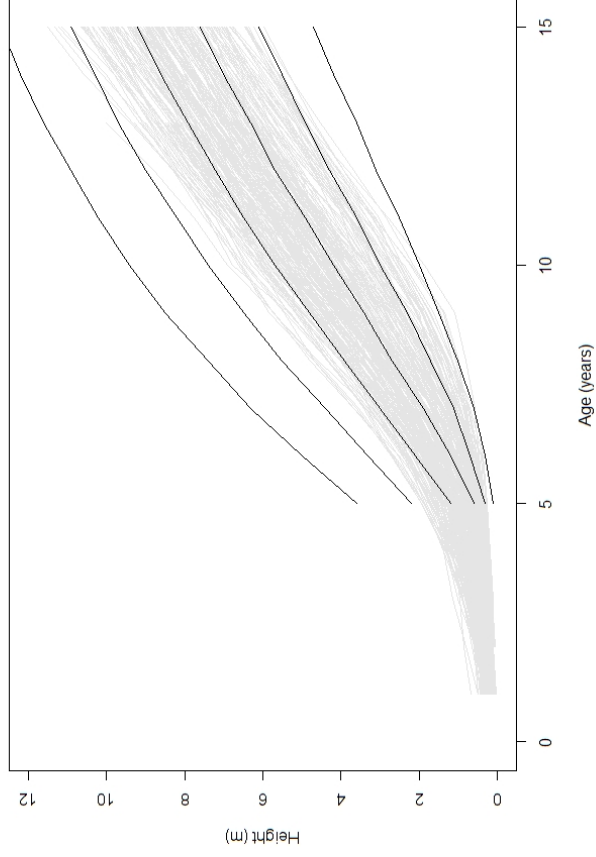
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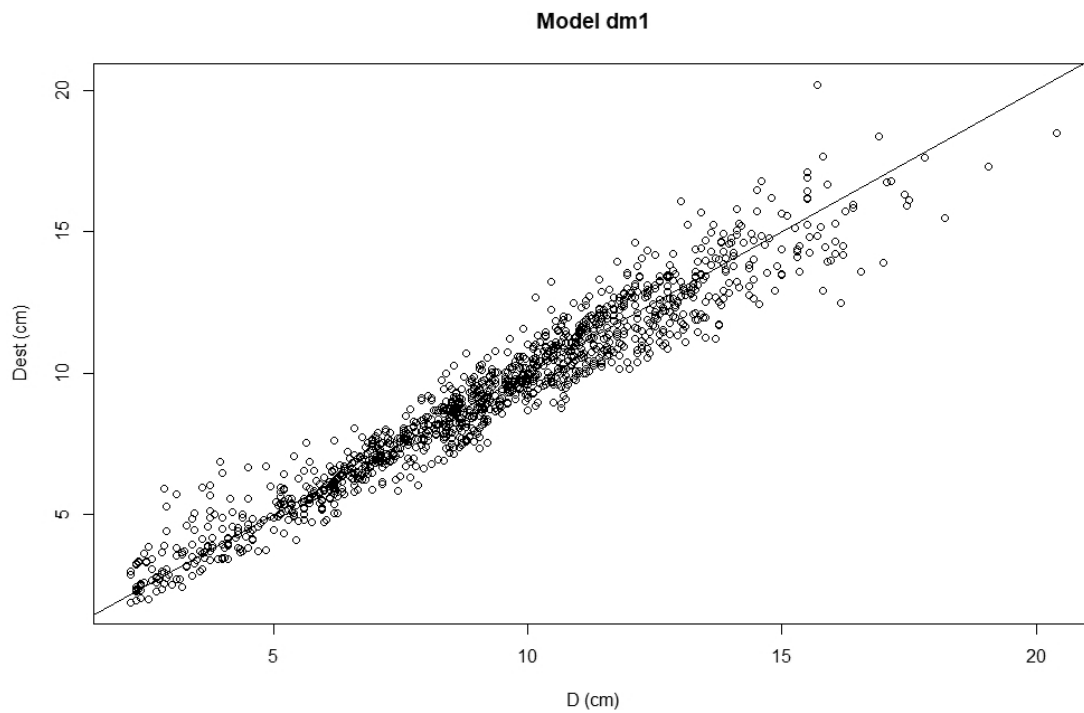
F13



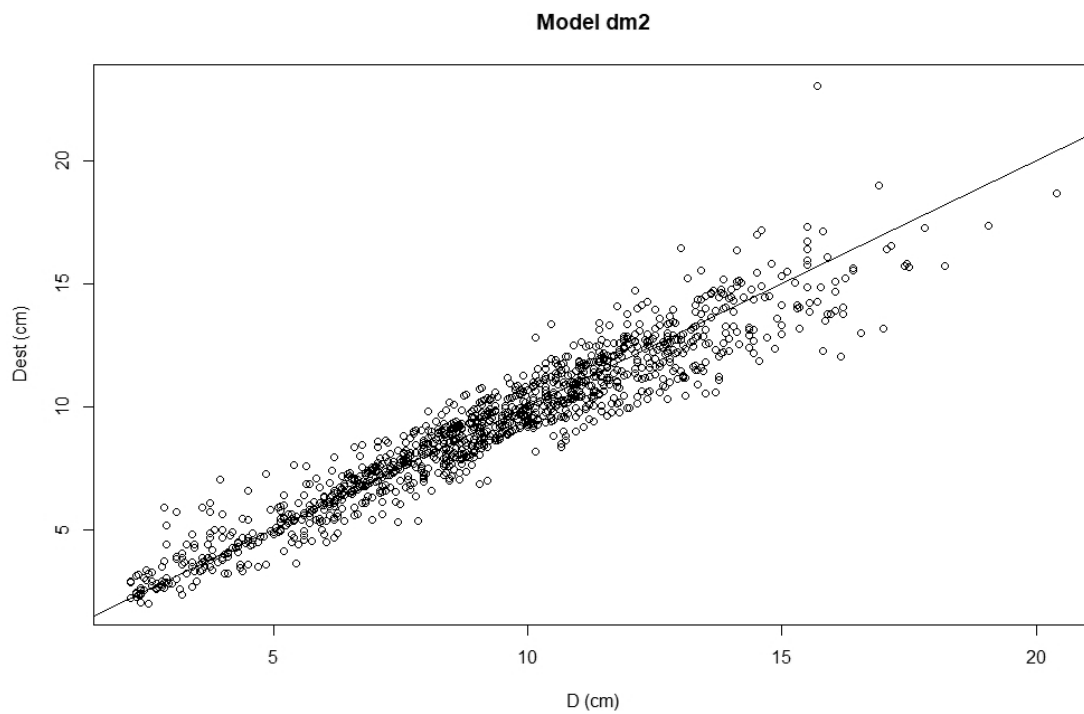
F15



Appendix 2. Linear regression models for DBH

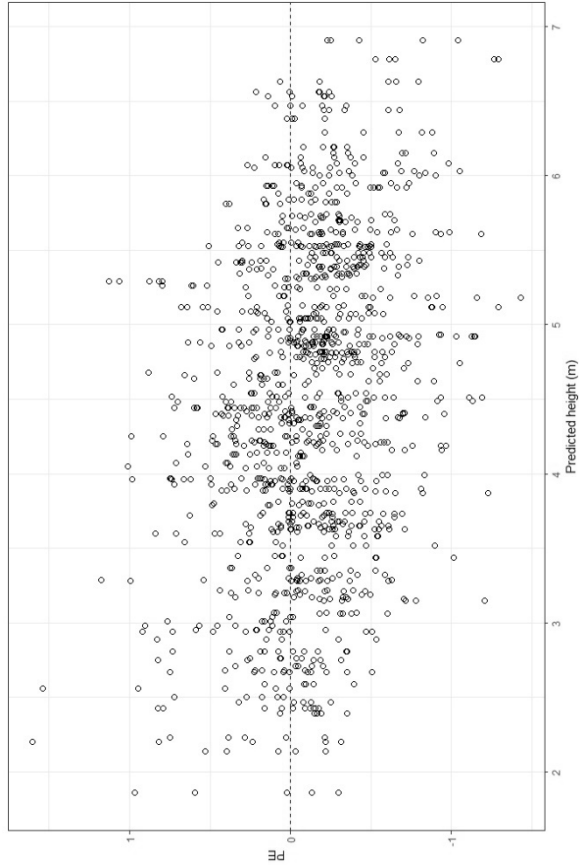


Six-parameter linear regression model md1 for DBH

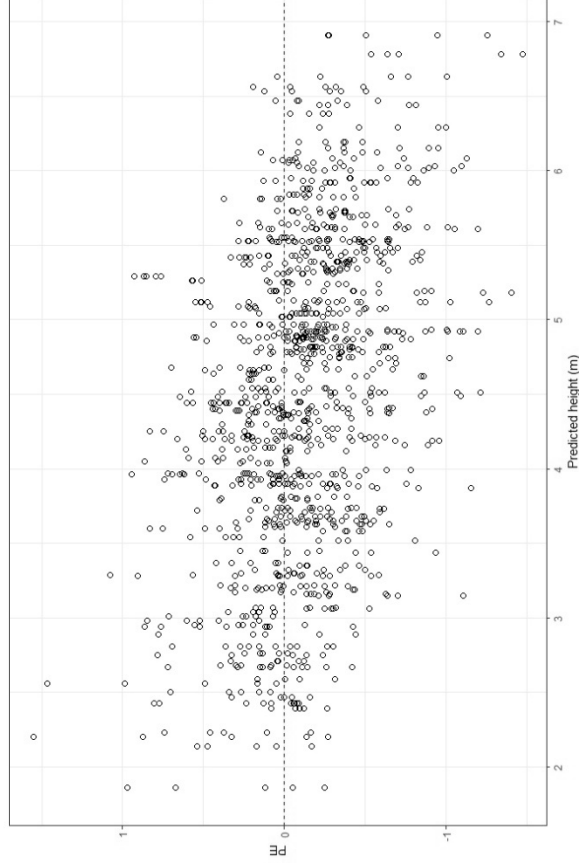


Four-parameter linear regression model for DBH

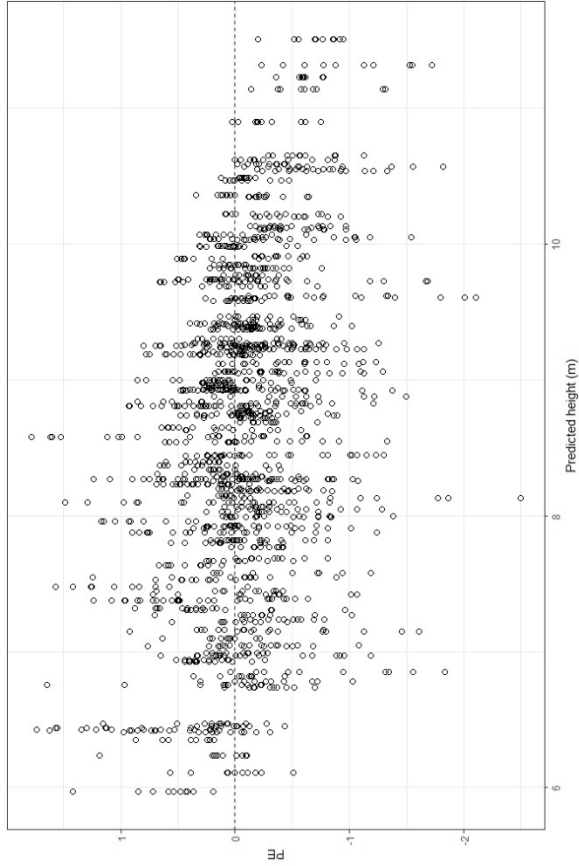
Appendix 3. Residual graphs for height development models



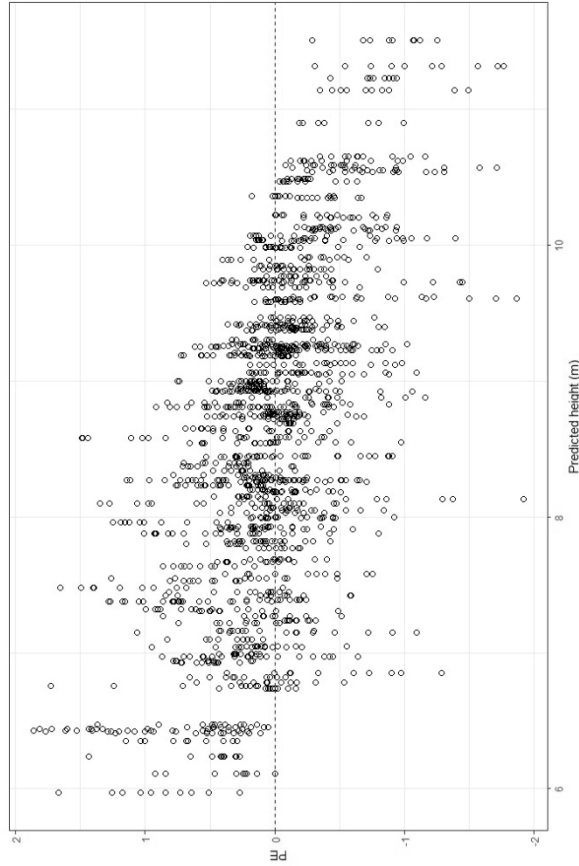
Residuals vs predicted height at the age of 10 years for Chapman-Richards model



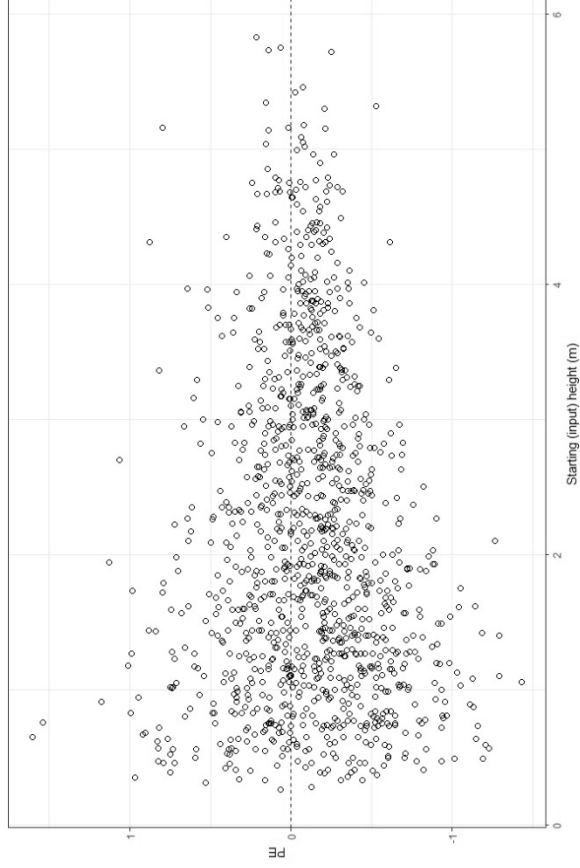
Residuals vs predicted height at the age of 10 years for Sloboda model



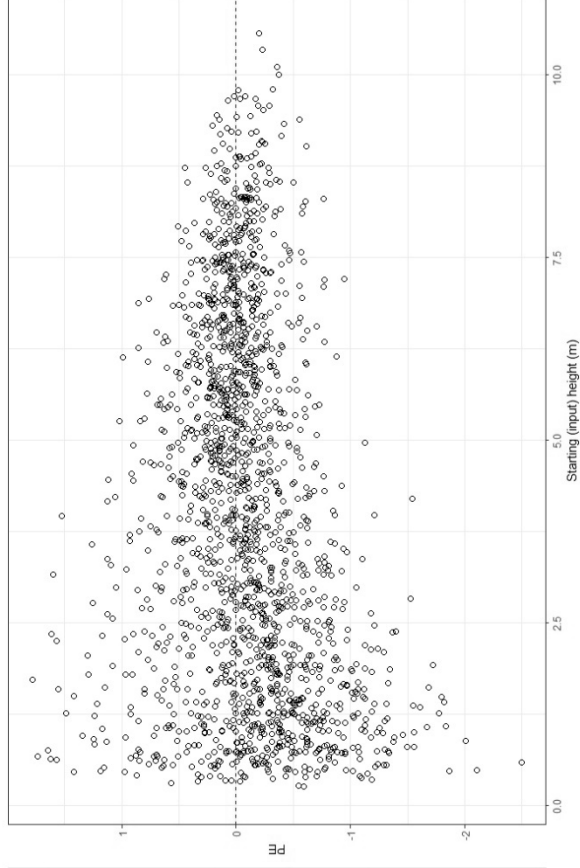
Residuals vs predicted height at the age of 15 years for Chapman-Richards model



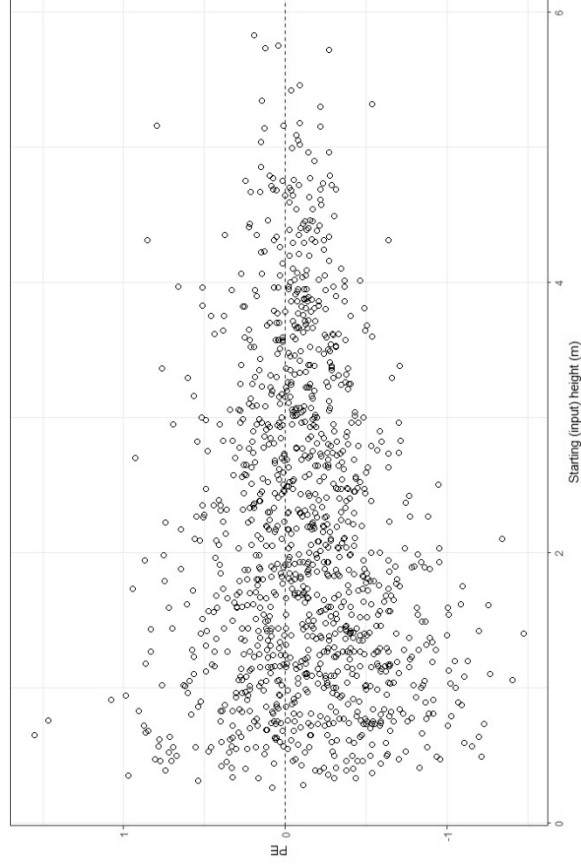
Residuals vs predicted height at the age of 15 years for Sloboda model



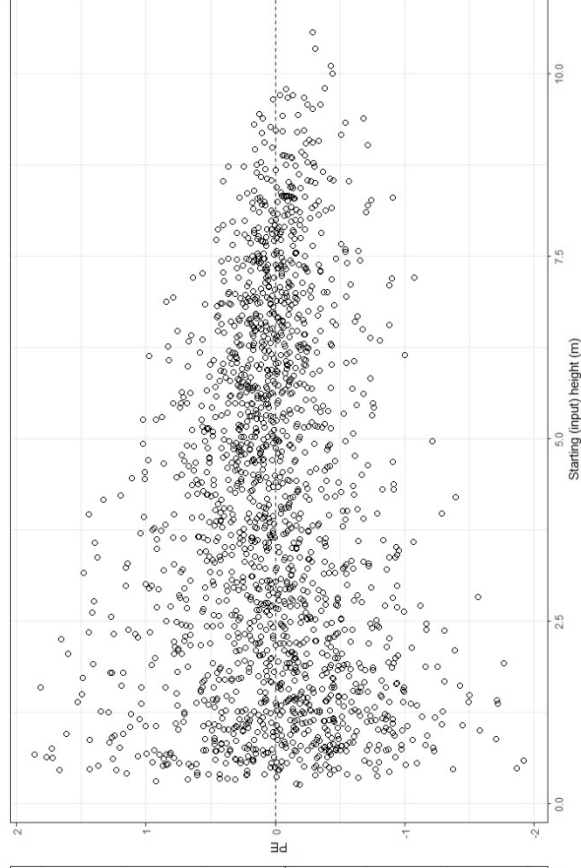
Residuals vs starting height, predicting height at the age of 10 for
Chapman-Richards model



Residuals vs starting height, predicting height at the age of 15 for
Chapman-Richards model

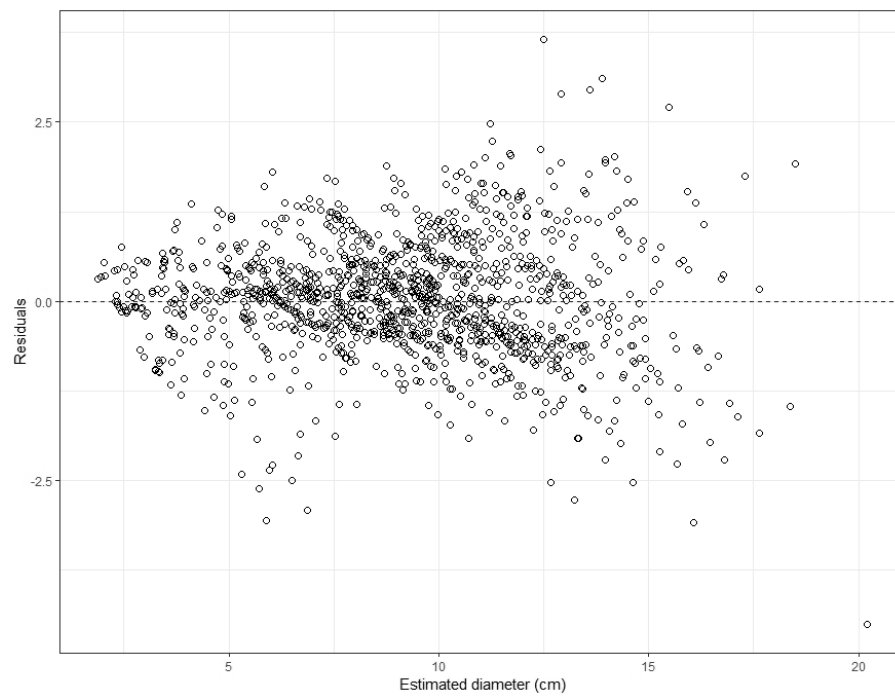


Residuals vs starting height, predicting height at the age of 10 for
Sloboda model

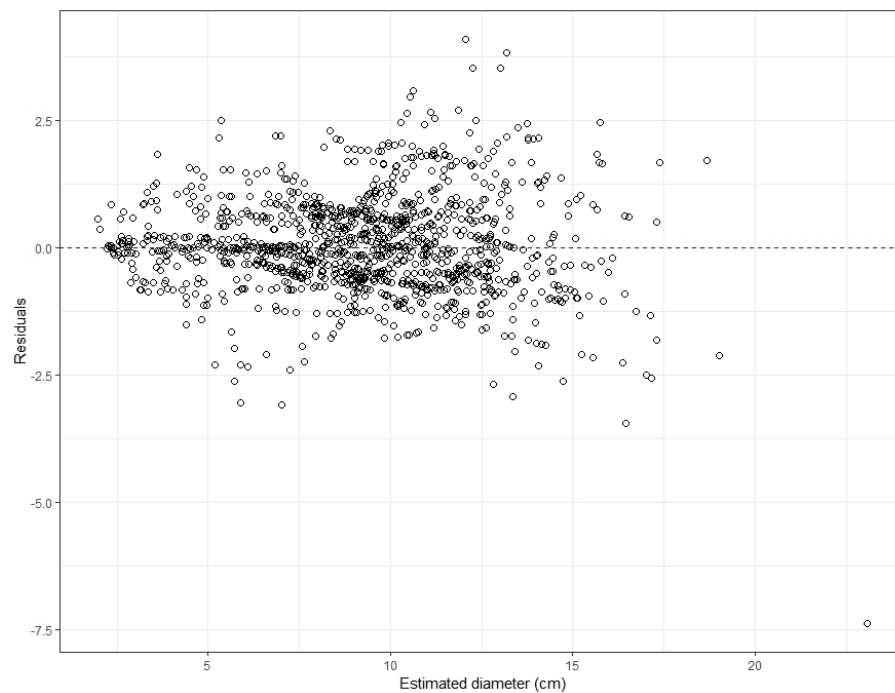


Residuals vs starting height, predicting height at the age of 15 for
Sloboda model

Appendix 4. Residual graphs for linear regression models dm_1 and dm_2



Residuals vs estimated diameter for dm_1



Residuals vs estimated diameter for dm_2